Augmented Reality and Novel Virtual Sample Generation Algorithm Based Autism Diagnosis System

University of Technology Sydney
Faculty of Engineering and Information Technology

Prepared By: Mohammad Omar Wedyan

Principal Supervisor: Prof. Adel Al-Jumaily

Co-Supervisor: Rami Khushaba

Submitted in partial fulfilment of the requirements for the Doctor of Philosophy

April 2020

Certificate of Authorship and Originality

I, Mohammad Wedyan, declare that this thesis is submitted in fulfilment of the requirements for the award of PhD degree, in the school of Biomedical Engineering, Faculty of Engineering and Information Technology at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature:

Production Note:
Signature removed prior to publication.

Mohammad Wedyan

Date: 16/04/2020

Dedication

To the Spirit of My Father

Acknowledgements

First and foremost, I thank ALLAH, the almighty, for helping me and giving me the strength and patience to complete this work.

I would like to express my sincere gratitude to my supervisor, Professor Adel Ali Al-Jumaily, for his continuous support over the course of my doctoral studies and for his patience, motivation, enthusiasm, and immense knowledge. His guidance was of tremendous help during my research and much appreciated. I could not have imagined having a better Ph.D. supervisor and mentor.

I would like to sincerely thank my dear and loving mother, Buthaina Al-Nasser, for her continuous support and prayers.

My deep gratitude is extended to my wonderful wife, Enas. Her support, encouragement, quiet patience, and unwavering love have undeniably been the bedrock upon which the past ten years of my life have been built. Her tolerance of my occasional dark moods during my studies is a testament in itself to her unyielding devotion and love. Also, I thank Enas's parents, Mr. Anas Al-Omari and Mrs. Dalal Al-Omari, for their unstinting encouragement and support.

I thank my colleagues: Raed Khalil, Mohammed Jaddo, and Muneer Al-Zubi. They are a great and supportive team.

Thank you to my wonderful children, my daughter Leen, and my sons Yazan and Ghaith who have decorated my life and made it full of happiness and joy.

Finally, this thesis is dedicated to the spirit of my father Omar Wedyan, who sadly died during my studies.

May Allah grant him his highest paradise (Amen).

Mohammad Wedyan.

December 2019, Sydney

Abstract

Creating a friendly and effective environment for diagnosing autism in children is a challenging research topic. This thesis proposes a diagnostic system for autistic children based on their upper limb movement. This new system has been designed based on using Augmented Reality (AR) to provide a friendly, effective, and interactive environment to perform the required diagnostic exercise and record the movements without any tension.

The other challenge in relation to this research topic is the size of the available clinical data. The clinical samples are generally small in this field of medical research due to the intrinsic prevalence of disorders and other factors such as elevated costs for patient recruitment and the limited time available for evaluations. Small sample sizes significantly limit the ability of pattern recognition methods to correctly predict or classify the data and this in turn leads to inaccurate classification performance. Thus, this thesis focuses on providing a technique to deal with the small data size and this is based on augmented data from a small real dataset.

The proposed new system employs many algorithms for diagnosing autistic children based on classification of the collected data from the AR system. For example, Linear Discriminant Analysis (LDA) is used for extracting the features from raw data, while Extreme Learning Machine (ELM), Support Vector Machine (SVM), and Softmax algorithms are used for classification. Also, the thesis uses deep neural networks, which are regarded as successful learning tools for building nonlinear models.

A robust classification model and a deep learning neural network needs a large dataset. This is because classification models are often unstable when they employ small datasets. Therefore, this thesis proposes a novel Virtual Sample Generation (VSG) algorithm in order to solve this issue. In respect of autism detection, it is difficult to obtain a large

dataset. The results show that when virtual samples are generated based on small samples, the accuracy of the autism diagnosis is enhanced from (84%-95%) compared to traditional methods. In addition, the proposed technique has a proven ability to be generalised as it can be tested with benchmark datasets such as the Breast Tissue dataset and Escherichia coli (E-coli) dataset. Indeed, the results show that the classification model that uses virtual samples is more accurate than to the model that uses original training data without virtual samples.

The required data for the system testing has been collected from different sources; we gained the ethical approval number ETH18-2710 from the University of Technology Sydney, titled "Implementation of an Augmented Reality Game to Track Upper Limb Movement in Autistic Children." In addition, this research was conducted in collaboration with the National Database for Autism Research (NDAR) in the USA, and the Scientific Institute IRCCS Eugenio Medea in Italy. Both institutions provided access to the database on the kinematic analysis of upper-limb movement in children with autism and typically developing children.

The main contribution of this thesis lies in designing a new system based on AR for diagnosing autism that does not require wearable hardware sensors. This factor makes the new system more generally applicable and comfortable. Furthermore, this thesis proposes a virtual sample generation algorithm to generate a virtual sample in order to enhance the accuracy of the classification when using deep learning networks that depend heavily on the amount of data. This innovation leads to more accurate diagnostic results.

Table of Contents

List of Figures

List of Tables

Abbreviations

AR	**Augmented Reality**
ASD	**Autism Spectrum Disorder**
DNA	**Deoxyribonucleic Acid**
EEG	**ElectroEncephaloGram**
ELM	**Extreme Learning Machine**
FVP	**Functional Virtual Population**
GA	**General Anesthesia**
HCI	**Human Computer Interaction**
HR	**High Risk for autism**
HRI	**Human Robot Interaction**
IRCCS	**Scientific Institute for Research, Hospitalization and Healthcare**
KBD	**Kashin Beck Disease**
LDA	**Linear Discriminant Analysis**
LR	**Low Risk for autism**
MTD	**Mega Trend Diffusion**
MVN	**MultiVariate Normal synthetic**
NDAR	**National Database for Autism Research**
RG	**Related Group**
SS	**Selected Samples**
SVM	**Support Vector Machine**
TD	**Typically Developing children**
UCI	**University of California, Irvine**

URG	**Unrelated Group**
VR	**Virtual Reality**
VSG	**Virtual Sample Generation**
MRI	**Magnetic Resonance Imaging**
ML	**Machine Learning**
NN	**Neural Networks**
CAE	**Convolutional Auto-encoders**

Chapter One
Introduction

This thesis aims to contribute and develop automated and child-friendly diagnostic systems for diagnosing autism. In this chapter, the background and motivations for the thesis are presented, including an outline of the problems to be addressed that will be expanded upon later in the thesis. The thesis questions will also be stated, including the reasons for their importance, and a chapter-by-chapter synopsis of the thesis contents will be provided.

1.1 Background and motivation

Diagnosing autism requires providing a suitable environment for the child (e.g., a safe warm and inviting space rather than an environment that induces the child to feel uncomfortable and tense). Accordingly, the autism diagnosis environment is critical. However, this type of environment imposes restrictions on the use of some types of technology, such as technology that employs annoying lights or frightening sounds. The monitoring of children's behaviour is routinely carried out by a medical doctor in a clinic. Diagnosis of autism can only be performed at limited times and it is likely to be overseen by a medical doctor; A child's behaviour differs if someone monitors him. Thus, the autistic specialist can overestimate the actual autism rate. Therefore, a technological solution which can monitor all actions in a less intrusive way is highly desirable.

Previous studies and applications for the measurement of the upper limb movements of autistic children have sought to extract trajectory information from simple limb movements. This information is gained through the use wearable sensor-based technology. This technology generates rich appearance information and extracts important details from simple movements, often permitting their full identification. While it may be desirable to employ wearable sensor-based technology, it is unacceptable in applications where friendly environments are paramount. This because such sensors make the children uncomfortable. Recent advances in sensor-based technology have led to the development of small sensors. These sensors are ecological, non-obtrusive, and can be easily embedded into objects but they may still be unacceptable for use with a lot of the children.

For this reason, this Ph.D. research focuses on employing augmented reality to design a child friendly environment that allows for child movement without any tension. Augmented reality enables specialists to diagnose autism based on 3D objects that are attractive to the child. A significant trend in augmented reality is to use this technology for both the diagnosis and treatment of autism. The challenge posed by AR in autism diagnosis and treatment is major since AR design relies on the targets' appearance and reality to produce a friendly environment.

In the first stage of this thesis, we investigate the possibility to diagnose autism based on upper limbs' movement information. Because there is only one study that has investigated this hypothesis [1], the thesis conducts experiments which employ the datasets of the National Database for Autism Research (NDAR) in the USA and the Scientific Institute IRCCS Eugenio Medea in Italy, and the latest data that we have collected. The results show that we can depend on the upper limbs to help to diagnosis autism, which agrees with the above-mentioned study. This stage uses a Linear Discriminant Analysis (LDA) for feature extraction. Then the classification is performed by using two machine-learning approaches; Support Vector Machine (SVM) and Extreme Learning Machine (ELM).

To choose and simulate a task or game and in order for it not to be a random selection, we evaluate three different tasks. These tasks are: firstly, to throw a small ball into a transparent plastic box and then insert the ball into a clear tube open at both sides; secondly, to place a block into a large open box, and then place it into four similar blocks on a target block to make a tower, and thirdly; to insert an object into a box with interchangeable lids. The study introduces machine learning to discriminate between children with autism. The results show maximum classification accuracy in terms of the task where the ball is inserted into a clear tube open at both sides.

In the implementation step, in this phase, the proposed environment and the new tracking system were implemented. We have implemented an environment that aims to present a child-friendly and effective environment. The model employs Augmented Reality (AR) to create virtual objects to encourage the children to starting moving their hands. The new system implementation is done by using Unity as an AR design tool.

Also, we have implemented the new tracking system that aims to measure the upper limb movements to diagnose children with autism by using C# as a programming language and the Microsoft Kinect as a clinical tracking tool, which is a low-cost solution. The solution starts by providing a customisable platform for autistic children which is controlled through the children's hand movements, then it tracks and records all the children's upper limb movements.

The latest trends in Human-Computer Interaction (HCI) were used to create this project, and kinematic data were recorded by Microsoft Kinect. As well as encouraging the children to interact, the use of AR for recording the movements of children in a child friendly environment is inexpensive and useful. The system offers simple approaches to solve complex issues which were previously faced when monitoring and tracking the actions of autistic children. Furthermore, the system may be helpful for other researchers in different fields of research and may provide a foundation tool for many different kinds of future research.

In the analysis step, the collected data is analysed by machine learning algorithms. For example, Linear Discriminant Analysis (LDA) is used for extracting the features from raw data, Extreme Learning Machine (ELM), Support Vector Machine (SVM), and Softmax algorithms are used for classification.

The deep neural networks are successful learning tools for building nonlinear models however they require a large dataset. Accordingly, they are often unstable when using small datasets. Therefore, to solve this issue, researchers have developed several approaches, one of which employs virtual samples. In medical studies, such as autism detection, it is difficult to collect a large dataset. So, this study proposes a virtual sample generation algorithm (VSG) to overcome the finite sample size.

The proposed algorithm works to improve classification performance significantly when working with a small dataset. The results show that when virtual samples are generated based on small real samples; the accuracy of autism diagnosis is enhanced compared to traditional methods. This study provides a new and reliable approach for a limited sample size issue. The proposed technique has proved it can be generalised by testing it with different benchmark datasets, and the results show that accuracy is enhanced compared to traditional methods.

1.2 Research questions and main contributions

Our research aims to address the following questions:

- Is there a difference between the upper movements of typical children and children with autism? If so, is it possible to diagnose autism on upper limb movement information?
- Is it possible to use augmented reality to create a child-friendly environment for diagnosing autism?

- Is it possible to track the movements of the upper limbs without any wearable sensors and obtain accurate measurements?
- How can we use deep neural networks even though we have a small data sample?

All these questions were answered in the affirmative. In terms of the first question, it was investigated in our four papers, which have been published in SSCI 2016 [2], IRIS 2016 [3], HIS 2018 [4], and the *International Journal of Hybrid Intelligent Systems* 2019 [5], these studies examined the possibility of diagnosing autism based on upper limb movements. Also, we evaluated different tasks in previous studies to know which task distinguished autism more than other exercises, and this was published in ISKE 2017 [6].

Relevant to the second and third questions, we implemented a system that aims to measure the movements of the upper limbs of children to diagnosis autism. The system used Augmented Reality (AR) to create virtual objects to encourage the children to move their hands and record their movements by the Microsoft Kinect (Kinect), which is potentially a low-cost solution.

The solution starts by providing a customisable platform for autistic children to design a task that is controlled through the hand movements of children. The latest trends in Human-Computer Interaction (HCI) are used to create this project, and kinematic data is recorded by Microsoft Kinect. As well as encouraging children to interact with our system, the system cheaply and effectively employs AR to design virtual objects and record the movements of children in a child-friendly environment without the use of any wearable hardware sensors. This research has been published in ABEC 2018 [7] and a new paper based on the research has been accepted for publication in *Multimedia Tools and Applications Journal*.

Relevant to the fourth question, we proposed a virtual sample generation algorithm to overcome the finite sample size and developed the proposed technique. The proposed algorithm works to improve classification performance significantly when working with small samples. The results show that when virtual samples are generated based on small sample, the accuracy of the autism diagnosis is enhanced, compared to traditional methods. Also, the proposed technique has proved its ability to be generalised by testing it with benchmark datasets such as the Breast Tissue dataset and Escherichia coli (E-coli) dataset. This study provides a new approach to a reliable model for a limited sample size issue, which has been published in *Algorithms Journal* [8].

In this Ph.D. research, the main original contributions have been 1) Designed and implemented a new child-friendly system based on AR to diagnose autism. 2) The tracking system worked without wearable hardware sensors and this makes the new system more applicable and comfortable. 3) Proposed a virtual sample generation algorithm to generate a virtual sample to enhance classification results by using deep learning networks that depend heavily on the amount of data, which leads to increased diagnostic results.

This research has led to eight papers, some of which have already been published. These papers are listed below:

1. M. Wedyan, O. Dorgham, and A. Al-Jumaily. "The Use of Augmented Reality in the Diagnosis and Treatment of Autistic Children: A Review and a New System". *Multimedia Tools and Applications Journal* (2020): 1-47.
2. M. Wedyan, A. Al-Jumaily, and A. Crippa. "Using Machine Learning to Perform Early Diagnosis of Autism Spectrum Disorder Based on Simple Upper Limb Movements". *International Journal of Hybrid Intelligent Systems* Preprint (2019): 1-12.

3. M. Wedyan, A. Crippa, and, A. Al-Jumaily. “A Novel Virtual Sample Generation Method to Overcome the Small Sample Size Problem in Computer Aided Medical Diagnosing”. *Algorithms Journal* (2019), 12 (8).
4. M. Wedyan, A. Al-Jumaily, and A. Crippa. “Early Diagnose of Autism Spectrum Disorder Using Machine Learning Based on Simple Upper Limb Movements”. 18th International Conference on Hybrid Intelligent Systems (HIS 2018), December 13-15, Porto, Portugal, 2018, PP. 491-500. Springer.
5. M. Wedyan, A. Ahmed, and A. Al-Jumaily. “Design and Implementation of an Augmented Reality Game to Diagnose Autism”. The Australian Biomedical Engineering Conference (ABEC 2018), October 7-10, Sydney, Australia. 2018.P. 4.
6. M. Wedyan and A. Al-Jumaily. “An Investigation of Upper Limb Motor Task Based Discriminate for High Risk Autism”. 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE 2017), November 24-26, Nanjing, China. 2017, PP. 1- 6. IEEE.
7. M. Wedyan and A. Al-Jumaily. “Early Diagnosis Autism Based on Upper Limb Motor Coordination in High Risk Subjects for Autism”. 4th International Symposium on Robotics and Intelligent Sensors (IRIS 2016), December 17-20, Tokyo, Japan, 2016, PP. 13-18. IEEE.
8. M. Wedyan and A. Al-Jumaily. “Upper Limb Motor Coordination Based Early Diagnosis in High Risk Subjects for Autism”. IEEE Symposium Series on Computational Intelligence (SSCI 2016), December 6-9, Athens, Greece, 2016, PP. 1-8. IEEE.

1.3 Significance

Herewith, we wish to restate the significance of the research that we have carried out, both from a scientific and an impact perspective. The main aim of this study has been to design a system that can solve the problem of recording and monitoring movements in child-friendly environments where comfort and serenity is paramount. We believe that this research is both innovative and can have a significant impact on entertainment and medical practice. Furthermore, the new system may prove useful for other researchers and provide the foundation for future research in different areas. This is because upper limb motion tracking attracts attention from both academia and industry due to its value in a wide range of applications. such as gaming, human-computer interaction and medical rehabilitation [9].

The conduct of this thesis has led to the development of three working prototypes:

1) A tracking and recording movement system; 2) an augmented reality system; and 3) a virtual sample generation algorithm. Each of these prototypes could potentially be extended into commercial software for the benefit of companies and end-users in real life.

The system can accurately track and register the specific details of the child's upper limb movements, and it works without wearable hardware sensors. This makes it more comfortable and effective, unlike other systems which track by observation; that is, they record a video of a child and then the child's movements are measured by observation. Furthermore, these other systems require many cameras and up to eight markers on a child's hand. The child also interacts with physical objects, and the wearable sensors measure the child's movements.

Moreover, our system enhances privacy because it is based on tracking joints without concern about the face; this extends the applicability of this technology to areas of application where privacy is vital such as patient monitoring in hospitals and care facilities. The outcome of this research has the potential to advance the knowledge base of this discipline with a comprehensive methodology to reliably monitor and detect human movement details.

1.4 Thesis structure

This doctoral thesis consists of five chapters (as shown in Figure 1.1)

1. Chapter 1 presents an overview of this research, including research issues, research motivations, research questions and contributions, research significance, and thesis structure.
2. Chapter 2 reviews the related research areas and especially addresses the research background concerning autism, autism definitions, economic costs of autism, early diagnosis. Moreover, the chapter reviews AR which includes definition, components, AR and autism, design features, summary for literature reviews, AR evaluation studies including single versus repeated interaction, sample sizes, structure versus free-form interactions, individual versus group experiments, data collection, analysis, and system implementation. Finally, it explores AR interaction experiments, its target, its tools and programming languages, its technique, challenges in the AR system studies for autism, discussion, future trends for AR for autism, and presents a literature review of machine learning to assist autism diagnosis.
3. Chapter 3 illustrates the new system and features procedures to design and implement an AR task to diagnose autism. The chapter includes an overview and related works. The method consists of system requirements, equations, description, design, implementation, expert feedback and pilot study, experiment, participants, procedure, data collection, data analysis, feature extraction, classification algorithm, the NDAR dataset, the IRCCS Eugenio Medea dataset,

performance of the classification algorithm, and evaluation. A conclusion and future work is provided.

4. Chapter 4 presents a novel virtual sample generation algorithm for a small sample problem in medical diagnosis in detail, including an overview of the problem, methods to overcome small datasets; including mega-trend Diffusion (MTD), Functional Virtual Population (FVP), Multivariate Normal Synthetic Sample Generation (MVN). Then the proposed method for virtual sample generation includes the pre-processing method and the technique, experiment, datasets, a review of experimental results, a numerical example, and a conclusion and future extensions.
5. Chapter 5 summarises the whole thesis and describes possible future research.

The rest of the thesis is organised as follows: Chapter 1 describes the research specifications, Chapter 2 briefly introduces the literature review on augmented reality with autism and machine learning with autism, Chapter 3 explains the proposed approaches for constructing our system. Chapter 4 describes the novel virtual sample generation method for the small sample problem in autism diagnosis. Chapter 5 presents the conclusion, results, future works, and publications.

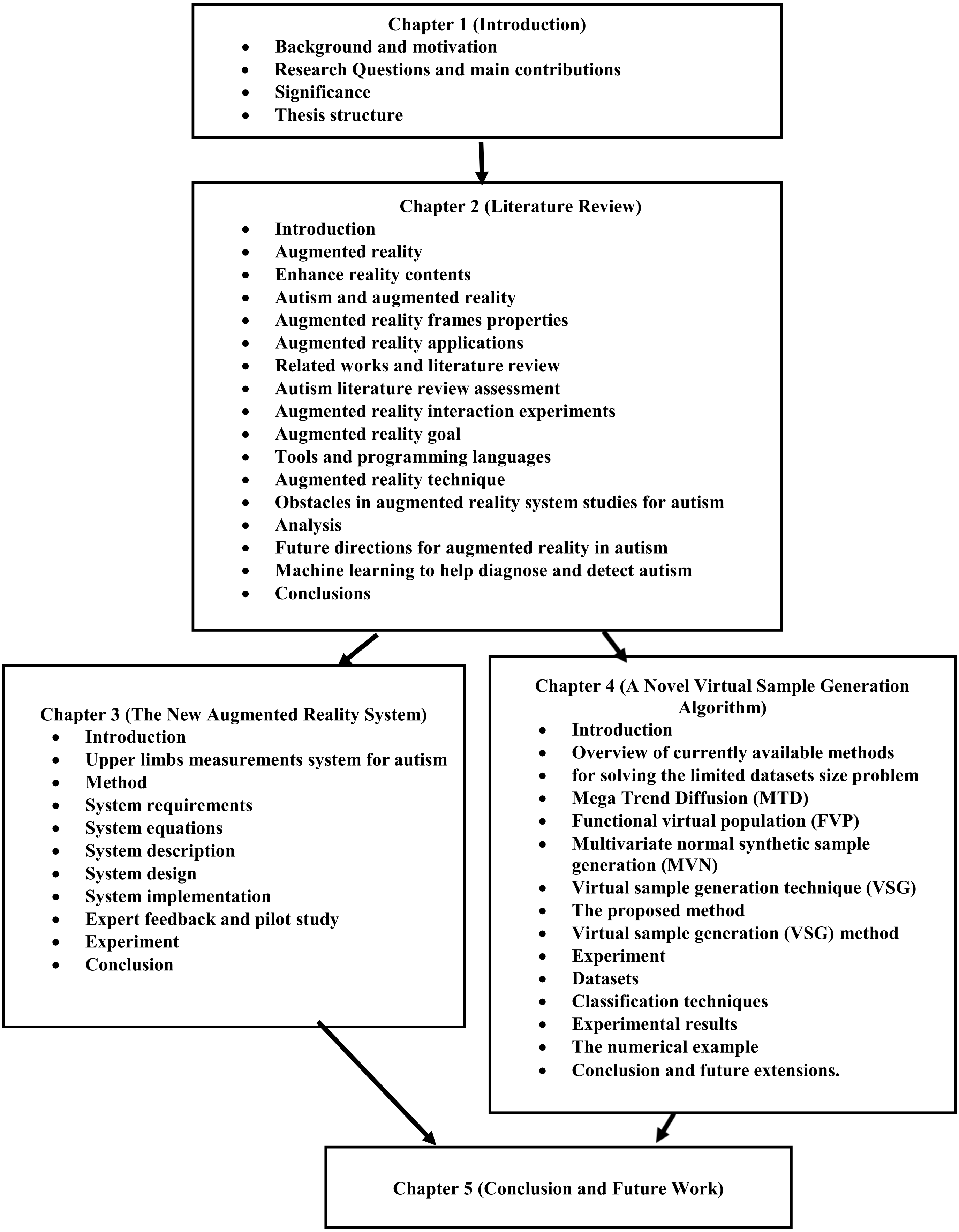


Figure 1.1 Thesis structure.

Chapter Two

Literature Review

(The content of this chapter has been published in *Multimedia Tools and Applications Journal*)

This chapter presents a review of the literature on the use of augmented reality (AR) in the diagnosis and treatment of autistic children with a particular focus on the efficacy of AR in assisting autistic children who have communicative, social, sentiment, and attention deficit disorders. The review also investigates interactions between AR systems and children, taking into consideration the target behaviours that are selected from the child during treatment. Such modes are fully explored by taking into account the needs of the individual child in terms of achieving an improvement in their condition. Most significantly, the empirical information that has been obtained from the reviewed works has been evaluated according to some specific targeted attitudes and how each AR solution was utilised during treatment to achieve the fostering of such attitudes in order to identify the requirements for building an effective AR system. In addition, the review reveals the essential design features that can enable AR systems to achieve a high level of effectiveness in autism therapy. The review also covers the instruction that AR systems were observed to execute and focuses on the significant characteristics that allow AR systems to accomplish degrees of efficacy in autism treatment. Finally, the review displays the classification of the various AR systems based on different criteria. The review ends by covering the use of machine-learning algorithms to assist autism diagnosis and prediction.

2.1 Introduction

In recent times, medical progress has led to remarkable enhancements in human physiological health around the world and has included the elimination of various kinds of deadly disease. However, correspondingly positive developments have not been seen to the same degree in the field of psychological health. Furthermore, there are many mental disorders that pose a real and constant danger to the well-being of many people and their families.

The huge expansion in the types and incidence of cerebral disorders globally seems to be a consequence of the complex interrelationship between psychological, social, and biological agents, as evidenced by World Health Organization statistics [10]. Based on the numbers it can be concluded that the presence of cerebral disorders has an impact on many people at different levels, from personal to economic and social because the regression and the hardship experienced by individuals impacts not just the individual concerned, but society as a whole.

Autism is a type of cerebral disorder and its typical symptoms include a distinct lack of social and language skills [11-13] repetitive behaviours [14, 15], lack of imagination or abstract thought [16], and emotion-processing deficits [17]. It is a disorder rather than an organic disease [18]. Furthermore, the prevalence of autism in the world is projected to increase rapidly in the years ahead, Figure 2.1 shows that the incidence of autism has risen steadily since the 1970s.

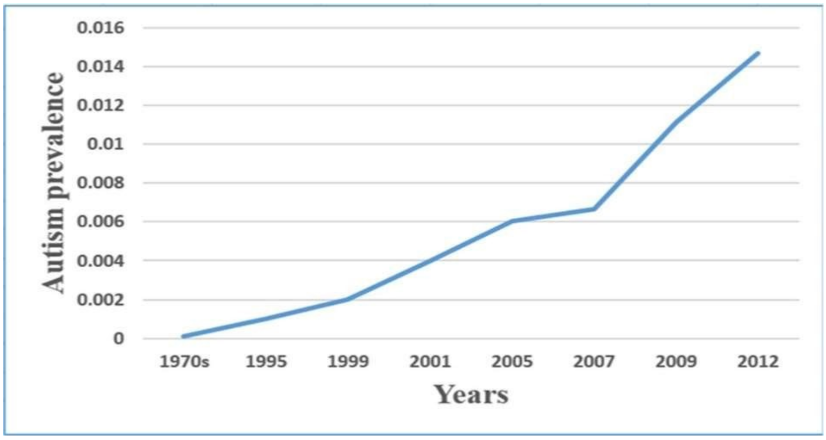


Figure 2.1 Autism detection has risen steadily [6].

In many respects, autism has a negative effect on the life of the individual in terms of their overall health, happiness, education, and social inclusion. It also has a detrimental effect on family life and wider society. A lot of these effects have an economic consequence that differs from one society to another [19-27].There are three main types of economic expenditure that are incurred in regards to autism. The first type is direct expenditure on, for instance, healthcare, social support, and education. The second type is indirect concealed expenditure on, for example, a decrease in income through loss of work. The third type of expenditure is informal concealed expenditure that is incurred [28-31], for instance, in taking care of an adult, child or infant with autism. It has been estimated that in the UK the lifetime expenditure to care for the needs of an autistic person is between £0.8 and £1.23 million according to the degree of functioning, while in the USA the total annual cost to the public purse is US$137 billion, and in Australia it ranges from AUS$8.1 to AUS$11.2 billion [28, 32].

It is difficult to determine the presence and the cause of autism without the assistance of specialised doctors and professional healthcare practitioners. Moreover, the attitudes and behavioural practices of the particular child play a significant role in arriving at an accurate diagnosis [18, 33, 34]. The diagnosis is, in part, based on the visual observation of the difficulty that a child has in terms of their contact and interaction with society.

Contact disorders include less visual contact, a taciturn attitude, and repeated activities [18, 35-40]. At present, the benchmark criteria [1] for diagnosing autism are as follows: (1) Clinical judgment based on observation and the use of indicators and behavioural scores for play activities and (2) meetings between the family and specialists or questionnaires filled in by the family of the child. There have also been attempts to determine the relevant neurobiological and attitudinal indicators for the prediction of autism spectrum deficits in order to identify a common phenotype among affected individuals and thereby enable the utilisation of computer-assisted profiling to aid diagnosis.

The importance of the work that continues to be conducted to improve diagnosis cannot be emphasised enough because the early discovery of autism spectrum deficits is incredibly important in terms of improving treatment outcomes [33, 41-43]. Early diagnosis leads to early intervention, which can enhance treatment outcomes and the child's overall development. In addition, early profiling provides knowledge for others, especially those who interact with a child who has autism spectrum disorder (ASD). The knowledge that can be gained from such work includes fresh data about primary contacting, enhanced theories on mental autism disorders and how they can be addressed through a structured pattern of intervention and learning, and a raising of awareness in terms of autism behaviours [44]. It is also important to note that an early diagnosis can hinder the development of indirect symptoms such as antagonism and self-harm. Such symptoms can become advanced when the main signs of ASD are not discovered. Early interventions to address the primary signs of ASD may prevent indirect signs from developing and reduce the necessity for more critical and costly interventions thereafter [43].

Recently, it has been argued that amusement technology may have huge potential in terms of enhancing the progress of the autistic child [14]. When applied appropriately, this type of technology can be used in leveraging the strengths and overcoming the weaknesses of the disorder, and can thus decrease the tension in autistic children that is created by real-world situations [45]. In a school setting for children with autism, it has been shown that this technology can have a positive effect on ongoing remedial procedures (e.g. [46, 47]). This technology has the ability to interact with autistic children through both generic human–robotic interaction (HRI) and human–computer interaction (HCI) [13,48].

To illustrate the mechanism of interaction technology studies on HRI (e.g. [49-57]) we tackle the interaction between robots and humans across a range of disciplines including engineering, computer science, sociology, and humanities (see Figure 2.2). On the other hand, studies on HCI (e.g. [47, 58-63]) investigate the interaction between computer software and humans. The research conducted on HCI revolves around comprehending as well as producing programs and other technologies that are desirable, usable, and effective for people. However, both HRI and HCI could be more useful and more effective if their respective advantages were combined (see Figure 2.3) [28, 49].

Figure 2.2 Human-robotic interaction [64].

Figure 2.3 Human-computer interaction [65].

Technical interaction has been a focus of attention for various studies. To clarify, schemes for technical interventions among children with ASD have been proposed. In the remainder of this first part of the chapter, a review is conducted to assess the competence of the existing technical interventions for children with autism. The review focuses specifically on AR systems that assist in the diagnosis and treatment of autistic children. In particular, it looks at the efficacy of AR in helping autistic children with their communicative, social, sentiment, and attention deficiencies. In addition, the review investigates child–computer/mobile interaction by considering the distinctive modes that are selected for treating a child with autism. These modes are examined by taking into account what the individual child needs in order to experience an improvement in their condition.

Furthermore, the empirical information in the reviewed works is evaluated according to the targeted attitudes and how each AR was utilised during a treatment period in order to enhance the targeted attitudes in order to identify the factors that are a prerequisite for an effective AR system. Moreover, the review highlights the essential design features that enable AR systems to achieve high levels of effectiveness in autism therapy. Also, the chapter provides some important guidance on how to implement an AR system, and the key design features that allow such systems to achieve a high level of efficacy in the treatment of autism. Then, the review concludes by classifying the various kinds of AR systems that have been developed based on different criteria.

2.2 Augmented reality

Augmented reality has many definitions (e.g. [48, 59, 61, 62, 66-75]). For instance, AR has been defined as a technique that supplies real and technical (computerised) items that both seem to cohabit real space [66]. Augmented reality has also been described as the adding of pictures, sounds, and other sensation augmentations to the reality domain in real time, thus allowing humans to interact with technical data inserted in the reality domain [68, 72]. It has also been defined as a structure that results from knowledge and skill where reality is augmented by technical components related to particular places and/or actions [73]. There are two main types of AR: 1) location-based AR and 2) visual-based AR. Location-based AR shows digital media to individuals when they use mobile phones and devices that have a global positioning system (GPS) (e.g. [76]). In contrast, visual-based

AR shows digital media to users after they have pointed their camera phone at an item [68, 77, 78]. However, irrespective of type, an AR technique must be able to [66, 79]:

- Maintain virtually generated items that are compatible with reality items.
- Perform efficiently in real time.
- Combine real items and virtually generated items together.

Virtual reality (VR) and AR are nearly the same. Both are efficient and immersive, and have data sensitivity. In VR, the user's scheme of reference is linked to a technical world, and through VR they sense a new world. In contrast, in AR, the user's scheme of reference is linked to reality but some technical items are added. Thus, the real and technical items appear to cohabit one world [48, 67, 80-82]. Some VR applications utilise touch apparatus, controllers and flexible devices [67]. Table 2.1 lists the main differences between AR and VR.

Table 2.1: The main differences between AR and VR [62, 83-86].

Augmented Reality	Virtual Reality
Supplies real setting with digital items	Completely immersed digital domain
The participant maintains a sense of existence in the real world	Participants feel like they are in a new domain
Requires a technique to join real and digital worlds together	Requires a technique to supply the technical world to the participant
Difficult to align real and technical objects	Difficult to make the VR world entertaining
Can include images and audio	Can include touchable apparatus, controllers and flexible devices

2.2.1 Augmented reality contents

Generally, the framework for an AR system consists of three main phases. The first involves tracking and registration, display technology and real-time processing. The second consists of interaction apparatus and procedures, as well as display and composition processes. The third is the application phase and includes an interface for the user. Augmented reality is a technology that deals with real time and three dimensions. Registration and tracking are considered to be the significant factors in creating a realistic AR image/scene [87, 88]. Figure 2.4 illustrates the typical AR contents.

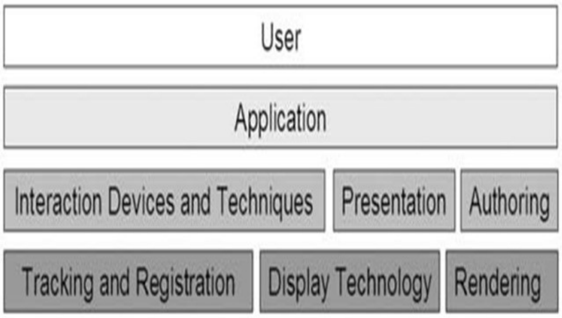


Figure 2.4 Building blocks for AR [87].

In an AR system, a GPS is utilised for tracking. Processing occurs in real time and the AR apparatus places a layer of graphics contents over the real domain in a rapid and factual-based manner [88]. Hence, quality authoring in AR is essential in creating a convincing visualisation of the connection between physical items and graphics objects to enhance the appearance of the AR environment [87].

2.2.2 Autism and augmented reality

Augmented reality technology is a good tool to use in assisting children with autism because it can help them improve their visual conceptualisation by creating technical components that relate to reality [89, 90]. Moreover, this technology has the capability to help autistic children not just in a medical or treatment sense. It can be used to involve the family including typically developing (TD) children as active participants in assisting their autistic family member [90]. Furthermore, AR can be utilised to improve the delivery of educational modules to students by utilising 3D virtual items. The utilisation of handheld devices in AR requires a phone apparatus, wireless connection, and position registered technology. That other immersive software products for education, such as risky sport, games, and imaginary world's proposal goals of attendance, reality, and immersion.

It has also been asserted that other dramatic profiles for education such as severe plays and technical world's proposal goals of attendance, reality, and enclosing, fill the vacuum between receiving education in official and unofficial settings and turning the invisible into the visible [88, 91]. By this, we mean that, in an AR environment, the user can see actions that would not otherwise be seen by the human eye, such as seeing atoms move in a liquid [92]. In addition, in AR children can repeat the exercises in their education modules freely as and when they like, thereby decreasing their reliance on instructors. Consequently, this can enhance teamwork. It also frees up the time of the instructor as they can rely on AR for basic and repetitive teaching activities, which means that they can offer multi-level programs to assist users in meeting their various individual needs [89]. This aspect would be very useful for children with autism who are very sensitive to reinforcement through, for instance, auditory and environmental stimuli [93]. Furthermore, it would be especially useful for those autistic children who find it difficult to interact with other people. Thus, AR has great potential as an assistive technology in improving the life outcomes of children with autism [51].

The design for an autism educational AR system should [71]:

- Be easy to use and interactive.
- Give the child clear, concise information.
- Allow the teacher to enter data in an easy and efficient way.
- Allow simple interactions between autistic children and teachers.
- Clarify difficult techniques to autistic children and teachers.
- Be cost-effective and easy to update.

An accurately designed and easily controllable display for the AR system is also necessary in order to prevent instructors from being constrained by technical issues which would reduce their ability to focus on teaching and learning activities [71].

2.3 Related works

This section surveys previous works related to augmented reality and autism. Table 2.2 provides a summary of the various AR systems that are discussed in this chapter. These systems are currently being used throughout the world to address the needs of autistic children, and they have been shown to have various degrees of success, as well as different properties, appearances, aims, and methods of intervention. Each one aims to stimulate particular kinds of attitudes among the treated children. Some of the key aspects of these systems are highlighted in the following review of the relevant literature.

Table 2.2 : Summary of the procedures and outcomes in the relevant literature on AR.

Paper	Procedure	Outcome	Practice/ Play/ Education
Bai et al, [59].	Influences of the AR technique in improving simulation play. Marker-based tracking.	Useful influence of raised educed simulation which plays an important role in repetition, time and engagement with the AR creates a range of play.	Play
Lakshimiprabha et al, [61].	Hand detection by the usage of Adaboost classifier Tracking utilising Kalman filter.	It presents a competent execution of the system.	Practice
Quintana et al, and Escobedo et al, [47, 69].	They utilised both tangible tags with accelerometers linked to the items of concern to observe participants' intervention with the item, and visual-based technologies to recognise the item.	It increases the time participants stayed on a mission by 20%. It increases positive emotions among participants, which, in turn, has led to increasing treatments to 24%. Participants gained efficient behavioural skills.	Practice
Bai et al, [94].	Marker-based tracking.	The positive effect of AR on ASD. The child prefers simulation playing instead of real playing.	Play
Bhatt et al, [67].	Movement tracking utilising the "Green Sock Tweening Platform".	It supports both focusing and imagining throughout, repeating motions and visual response.	Play
Escobedo et al, [95].	Vision-based algorithm for eye detection.	It facilitates training and education social skills, increases both the amount and goodness of social interventions and reduces social and behavioural mistakes.	Practice
Chen et al, [96].	Six face expressions that contacted basic feelings for the AR-based 3-D modeling of self-face expressions. Feelings were aligned with situations that the children had faced.	Children's observations were enhanced after utilising the AR. Enhanced sentimental expression and social experiences.	Practice

Mcmahon et al, [97].	The significance of such research is to determine the influence of the three directions such as a paper map, Google Maps on a cell phone, and AR navigation application.	The autistic child independence direction tests enhanced to an average of 95%, and the child navigated with 100% autonomy through the three AR sessions.	Practice
Chen et al, [98].	(AR)-based video modeling storybook (ARVMS).	Enhanced attention and social skills from (range: 30-53.75%) to (range: 93.57-98.57%).	Education
Mcmahon et al, [76].	The goal is to test the impacts of location-based AR and raise appointment chances.	The effectiveness of the intervention was 100%.	Practice
Mcmahon et al, [99].	Educate scientific vocabulary to university students with mental inability and autism.	Highly effective intervention 85%.	Education
Brando et al, and Cunha et al [60, 100].	Five various primary human emotions.	Will be executed later by the authors.	Play
Vullamparthi et al, [101].	-Mobile-based. -multimedia based technology. - based 3D image.	It was appreciated by parents (as expressed through feedback)	Practice
Baietal et al, [90].	Marker-based tracking.	Will be performed later by the authors.	Play
Casas et al, [102].	Participants' physical motions as a way for interaction (based on vision algorithms for movement detection).	A lot of activities were developed. Such as, learning about body section and body postures.	Play
Tentori et al, and Fevela et al, [46, 103].	The shouting amount existed in the schoolroom.	The system enhanced single and collective behaviour.	Play
Herrera et al, [104].	Pictograph.	Can enhance the care of autistic people.	Play
Richard et al, [105].	Marker-based tracking.	Participants were capable of expressing some good feelings when faced with the application.	Play

Cihak et al, [106].	Marker-based tracking.	The AR interaction was very efficient.	Practice
El-Seoud et al, [107].	Mobile-based. Marker-based.	Improving communication. Increase the focus. It enhances interaction and the attention of the child.	Practice
Lorenzo et al, [108].	Mobile-based Participants play with virtual object.	Slight improvements in flexibility and imitation.	Play
Tang et al, [109].	Mobile-based Deep learning Tensor flow.	Promising and satisfying results.	Play

2.4 Evaluation of studies

The issues facing researchers studying the use of robots for autism are largely similar to those facing researchers wishing to develop AR techniques for autism. Therefore, due to the scarcity of literature on AR and autism, it seems logical to examine the issue of the application of AR techniques for autism by evaluating the literature on AR for autism by using the same evaluation criteria that have been used in the literature on the use of robots for autism.

In the research studies that have investigated the use of robots to aid those with autism, there is weak cooperation between researchers regarding the selection of study populations and the methods applied. This lack of cooperation is high because of the geographical distance between study pools and the lack of cost-effective, commercially available autism-related robot platforms. Consequently, there is a difference in how researchers assess the use of robots for autism. The studies do not apply a set of standard procedures or criteria. Instead, they vary in terms of, for example, the number of interventions, number of users, types of intervention, and methods used to analyse the acquired data. Below, we provide an overview of some of the different criteria that researchers utilise in the assessment of socially supportive systems such as robots [51].

2.4.1 Single versus repeated intervention

Research studies differ in terms of the number of interventions that users have with AR. Autistic children are very sensitive to new information and alterations to patterns, so the degree of exposure they have to a device is important when evaluating the impact of a program on this type of user. Thus, an autistic user's first reaction to a program as a stimulus or motivating factor might be different to their reaction when they recognise the program. However, both single-intervention and repeated-intervention studies have their advantages and disadvantages [51].

From a logistical perspective, single-intervention studies are easy to execute. Moreover, they usually allow more users to be involved in the research, which augments statistical accuracy. In addition, single-intervention experiments can show how technology is initially perceived, which provides useful data for the development of socially supportive technology. When a user has prior exposure to technology becomes less significant than comparing the circumstances. Therefore, researchers allow the children to interact with the system before the experiment. Thus, innovation might be reduced by an interaction period through the children and the technology interventions [51].

On the other hand, studies that employ repeated interventions (e.g. [59, 69, 76, 90, 96, 98, 99, 105]) enable users to adapt to the technology and this gives the researcher time-based information. Although this time session is sensitive to modifications in a temper for a while. By using an effective number of experiments, studies can discover how attitudes develop and evolve when using the technology. Many types of research studies use the repeated-intervention approach and can take many weeks (e.g. [95]), especially when there are two to five interventions for every user. Indeed, some studies can last for many months or even years.

2.4.2 Number of users

The use of a large study population usually leads to enhanced accuracy and enables researchers to test hypotheses about the efficiency of AR more precisely. Some studies on AR for autism have included relatively few children (normally three or four (e.g. [96]) or less (e.g. [94]). However, some studies have been able to use a big sample (e.g. [59, 61, 69, 95, 97, 98, 102]), thereby enabling researchers to study the actions and reactions of multiple users in a chain of unconstrained interventions.

2.4.3 Structured versus free interventions

A structured AR intervention (e.g. [59, 69, 96, 98, 102, 104]) for autistic children usually involves the presence of an adult (the researcher or a healthcare professional) who guides the child participants in undertaking pre-specified activities using the AR technique. On the other hand, free interventions (e.g. [61, 76, 90, 95, 99]) allow the child user to interact with the AR system with no input from an adult unless it is absolutely necessary.

2.4.4 Individual versus group trials

The results of empirical experiments on the interaction between users and AR might differ if they were based on a single user (e.g. [59, 61, 67, 69, 76, 90, 94, 96-99, 102, 104]) or many users (e.g. [95]). However, in their favour, one-to-one studies, where a single child reacts with one AR system, produce fewer contradictory variations (such as the attitude of other children) for the researcher to consider when evaluating the effect of AR. In addition, it is easier to identify the type of interactions that occur by only having one user. On the other hand, the many-to-one study can be conducted as a free or structured intervention in an everyday environment, such as a school, and it can be used to assess the interactions of two users with a single AR or the interactions of many users with a single AR. This type of group study enables the researcher to gauge the influence of AR on a person-to-person basis. However, thus far, nearly all of the studies on AR have been one-to-one studies. Nevertheless, a notable proportion of autism treatments and some experiments have been designed for both single and pooled samples (e.g. [95]).

2.4.5 Information gathering and analysis

The data collection and analysis procedure in this field can be based on either a qualitative (e.g. [59, 61, 69, 94, 95, 98]), or quantitative (e.g. [67]) approach. The former approach is descriptive and involves some form of tracking or monitoring of the participants, whereas the latter approach focuses on statistics. As autism is a mental and behavioural disorder, it is determined and treated on the basis of attitudinal monitoring by a qualified healthcare professional [51].

2.4.6 Augmented reality-based technique

The marker-based tracking system is utilised in AR applications to create graphics objects (e.g. [59, 90, 94]); this system is based on a predefined marker. It is an accurate method and it can be used to expand the number of graphics objects in the AR system because it is very easy to observe outcomes against the marker and make any necessary changes. In contrast, model-based tracking observation requires the use of prebuilt 3D designs. It is a flexible and creative method, but it is less easy to redesign, is still generally unreliable, requires user intervention, and has a high number of computation requirements.

2.5 Augmented reality interaction experiments

Table 2.3 summarises the types of experiments that are used to assess the interactions between children and the various AR systems discussed in this chapter. As mentioned above, a child may interact with the system alone (individual) or a group of children may interact with the system (group) at the same time. They may have a guide (structured) or interact with the system without the presence of a teacher (free). They may interact with the system only one time (single) or multiple times (repeated). In addition, Table 2.3 shows the target skills and describes the interactions between children and these systems.

Table 2.3: Summary of targets and methodologies used in the relevant literature.

Paper	Individual/ Group	Structured /Free	Target	Single/ Repeated	Participant (age)	Tools and Programming language
Bai et al, [59].	Individual	Structured	Imagination	Repeated	12 (4 -7) Years	Goblin XNA
Lakshimiprabha et al, [61]	Individual	Structured	Attention. New skills and knowledge	Repeated	5 (5 -12) Years	OpenCV
Quintana et al, and Escobedo et al, [47, 69]	Individual	Structured	Attention Emotions	Repeated	50 (3 - 8) Years	RFID
Bai et al, [94].	Individual	Free	Imagination	NA	2 (4 - 5) Years	Goblin XNA
Bhatt et al, [67].	Individual	Free	Imagination. Social interaction Hand-eye coordination	Repeated	4 (10 - 15) Years	ActionScript 3.0 Adobe Flash CS6.
Escobedo et al, [95].	Both	Free	Social skills	Repeated	12 (8-11) Years	NA
Chen et al, [96].	Individual	Structured	Motional expression Social skills	Repeated	3 (10-13) Years	Vuforia
Mcmahon et al, [97].	Individual	Free	Improve travel and Navigation skills.	Repeated	6 (18) Years	Niftybrick
Chen et al, [98].	Individual	Structured	Strengthen attract Attention and social skills	Repeated	6 (11-13) Years	Vuforia
Mcmahon et al, [76].	Individual	Free	Improve travel and Navigation skills.	Repeated	4 (21) Years	Layer (2013)
Mcmahon et al, [99].	Individual	Free	Literacy skills and Acquiring vocabulary	Repeated	4 (25) Years	Aurasma

Brando et al, and Cunha et al, [60, 100].	Will be executed later by the authors.		-Emotions recognise -Facial expressions	Will be executed later by the authors.		OpenCV
Vullamparthi et al, [101].	Will be executed later by the authors.		Social interaction and communication	Will be executed later by the authors.	12	E-Saadhya
Bai et al, [90].	Individual	Structured	Imaginative play	Repeated	Will be executed later by the authors.	
Casas et el, [102].	Individual	Structured	Acquisition of certain skills	Repeated	5	OpenSceneGraph
Tentori et al, and Fevela et al, [46, 103].	Individual	Free	Awareness of their behaviour	Repeated	21 (7-14) Years	Web-based
Herrera et al, [104].	Individual	Structured	Attention and Imitation	Repeated	children and adults	NA
Richard et al, [105].	Individual	Structured	Examine specific behaviour	Repeated	93	C++ 6.0 OpenGL
Mekni et al, [88].	Individual	Structured	Check the impacts of AR	Repeated	3 (6-7) Years	Aurasma
Liu et al, [110].	Individual	Structured	Improving social and cognitive skills	Single	2 (8-9) Years	Brain Power
Sahin et al,[111].	Individual	Structured	Social communication	Repeated	1 (14) Years	Smart glasses
Sahin et al,[112].	Individual	Structured	Impacts of utilising AR. Interaction. Socio-emotional and cognitive skills.	NA	18 (4.4-21.5) Years	AR smart glasses. BPAS.
El-seoud et al, [107].	Individual	NA	Education Environment	Repeated	3	Aurasma

Lorenzo et al, [108].	Group	Structured	Improve social skills	Repeated	11 (2-6) Years	Quicker Vision
Tang et al, [109].	Individual	NA	Vocabulary Learning	NA	NA	NA

2.6 Objectives of augmented reality systems for autism

Augmented reality techniques possess several important functions that are useful in the treatment of autistic children. In autism treatment, AR can perform many functions, even in the same treatment session. Through the use of games and exercises, AR is able to interact with the child to inculcate skills as well as particular desired behaviours. It can also facilitate reinforcement and favourable responses in the effective execution of a small task. Based on the works we investigated, we have classified the objectives or aspects that AR systems should seek to address in order to improve the lives of children with autism as follows:

- **Imagination:** This aspect is related to mind theory as it relates to reproducing a graphical imagining of the facets of an imaginary world that would otherwise be contained entirely within the human mind. Pretend or fantasy play is one method to express imagination [113]. Yet autistic children encounter different obstacles in regard to fantasy play [113, 114]. Their participation in this sort of play activity usually seems purposeless, and they usually iterate actions without alteration [114]. Autistic children have a lot of similar play desires and capabilities for play, friendliness, and peer-group acceptance as TD children [115]. The level of aloneness experienced by the autistic child appears to be significantly related to peer group reactions to them [114].
- **Attention:** This objective relates to the autistic child's propensity to focus on chosen objects from their surroundings, to the exclusion of others around them

[116]. While this is not a characteristic that proves the presence of ASD, it is the first symptom of ASD in infants. Recently, studies have analysed ways to use eye-motion records and alteration-discovery techniques to identify and address autism in children [117]. A basic computer program can augment concentration. Occasionally, it can, in comparison with conventional educational methods, lead to increased learning among a lot of autistic children [118].

- **Social skills:** In the context of this study, the term 'social skills' refers to those attitudes that, in similar situations, anticipate significant social effects among children and youth [119]. Social skill disorders are still a difficult area in AR in terms of meeting the needs of autistic persons. Previous studies that have tested attitudes have tended to concentrate on experiments that include making eye contact and exchanging hugs. The results of some of these experiments seem to be encouraging in terms of aiding the young autistic child to acquire social skills and in directing them toward a natural social attitude that is compatible with the attitude of their compeers. For example, benefaction of adult and peer involved interventions, peer forming and starting by an autistic child, class extent educating or interaction, and the utilising of scripts [120].
- **Emotion:** This aspect is depicted as a running method for flexible adaptation; it fulfills both aims of being able to quickly exhibit appropriate reactions to situations and of giving breaks for re-evaluation and intention contacting in the advantage of response improvement [121]. The standard feelings experienced by humans are excitement, sorrow, astonishment, fury, abhorrence, and fright [122]. Autistic children find it hard to sense these emotions [123, 124]. However, AR has the potential to educate autistic children to identify and realise these types of feelings [124]. Some research outcomes have indicated that it is likely that autistic

children can learn how to both evaluate such feelings in others and also realise these feelings in themselves (e.g. [124]).

- **Navigation skills:** These skills are required by humans so that they can get from one place to another. Direction assistance is a method by which an autistic child can be supplied with information about their direction needs, which enables them to have a better quality of life and a higher level of happiness [125]. Autistic children may decide to visit and contact acquaintances by using public transport. Hence, flexible methods of showing the necessary information via a navigator application in a mobile device can enable these children to have instant access to the context-related information that is the most helpful in meeting their demands. The currently available mobile devices can support navigation applications because of their acceptance among those with disabilities. This sort of technology could be utilised for tasks other than navigation. It is a promising technology for disabled people, because of its interactive features, and the wide availability of mobile devices in society [97].

2.7 Tools and programming languages for augmented reality systems

Information technology (IT) is evolving at a rapid pace and this has led to a lot of new branches of IT over the last two decades including, notably, AR technology. However, it takes a long time to design an AR application and the designer or programmer needs to undertake low-degree programming, component development and enhancement to create such an application. These applications also require the utilisation of suitable devices. Moreover, these devices need to be faster and more cost-effective if the developed AR applications are to be used by the general population [126].

Nevertheless, more business use cases of AR are appearing as the technology develops, leading to an increased demand for tools and programming languages that can create AR apps for enterprises. From our review, the most popular tools and programming languages for AR development currently are Goblin XNA (e.g. [59, 94]), Aurasma (e.g. [99, 107]), OpenCV (e.g. [60, 61]), and Unity (e.g. [96, 98]).

2.8 Tracking techniques in augmented reality

One of the main technical obstacles to creating an efficient AR system is saving the right recordings and observing the differences in people's interactions with real and virtual items [127]. A lot of tracking methods are utilised in AR. These methods can be automated, magnetic, immobile, ultrasound, or vision based. The enhancement outcomes that are based on vision-based methods are more accurate because these methods consider features that are pulled from images in order to be enhanced. There are two main types of tracking that can be employed in AR:

- Marker-based tracking, which is a very effective method [128, 129] because it enhances robustness and yet also decreases computation requirements [129]. It is simple to insert and remove markers from the real environment [94]. However, the main disadvantage of this method is that it requires ongoing maintenance [129].
- Marker-less tracking, which involves observing normal properties or their geometry [129]. The main disadvantage of this method is that it needs to consider participants' interactions or early offline calibration [129]. It also has a high computational cost.

2.9 Analysis of previous studies

In this chapter, we classified the development and use of socially supportive AR systems for autism treatment into three stages: AR system design, interaction procedure, and evaluation. Although AR schemes may differ substantially in terms of visual appearance, they all have the capacity to invoke new behaviours, such as concentration and imitation, among many autistic children. In this part of the chapter, we attempt to predict the outlook for this field of study. First, we focus on the obstacles facing socially supportive AR schemes for autism. Then we pinpoint some research directions that we think will lead to progress in this domain.

2.9.1 Obstacles facing studies on augmented reality systems for autism

One of the main weaknesses of all of the studies reviewed for this chapter is that the data have quality but no quantity. The trials conducted by these studies aimed to obtain a descriptive evaluation based on a sample of a few persons over a short time period of a few days or sometimes weeks.

Moreover, to achieve success in evolving and evaluating AR techniques for autism treatment requires the interdisciplinary cooperation of researchers who have specialised in computer science, HCI, sociology, and clinical study. Some study groups are able to perform a comprehensive analysis covering all of these different disciplines. Such groups tend to concentrate on their respective strengths. However, regrettably, without the involvement of therapists, most studies lack long-term, progressive access to target groups such as autistic children. This makes it difficult to gauge the advantages of proposed systems or to come to firm system design decisions and conclusions. Thus, simplifying the cooperation between clinicians and computer scientists is probably the only way to enable the sort of deep interventional research that would produce robust results.

The AR technique has recently been aimed at the domain of autism treatment. Hence, in testing, the applications have to interact with autistic children, and they have to be easy to use, attractive, and fast-reacting. However, the need to conduct research among this population group raises an issue that is related to behavioural psychology. Specifically, the researcher needs to be able to accurately understand the behaviours of a single child and then know how to contrast and compare that child's behaviours with the behaviours of other children. A lot of factors affect behaviour. For instance, temperament, time of day, and early life experiences can influence how a child interacts during a therapy session. Thus, finding a way to isolate the effects of an AR scheme on treatment is another obstacle that must be overcome in order to reinforce the comprehension of psychology for the community.

Many studies require expert psychologists to evaluate the status of the participants. However, a lot of training and experience is needed to be able to undertake this task. Thus, again, AR researchers have to cooperate with psychologists to gain insights into their study population and to ensure that their work is given credence in terms of its efficacy for autism treatment. This is also important because it will be healthcare professionals and psychologists who will be the actual users of these AR systems. Research on technologies for autism has evolved in recent times, but there is still a lack of data on how and to what extent AR systems affect autistic children. While this is not the fault of the researchers in this domain, there are some obstacles that still need to be overcome before it can be concluded that the use of an AR system can have a significant and positive effect in autism therapy.

2.9.2 Future directions for augmented reality for autism

Although the initial AR interface was evolved by Sutherland in the 1960s [130, 131], AR remains in the early stage of development, so the scope of future applications is potentially unlimited [132, 133]. However, the advances that have been achieved in the study of AR thus far are encouraging and they show promise for specific areas of education [89].

Through our investigation of state of the art AR systems for autism treatment, we identified various trends that we anticipate will enable AR to better discover and react to user actions. A recent emerging trend in AR systems for autism concerns AR systems that can discover user temperaments and moods and then select an appropriate response in order to help the user to adjust their behaviour accordingly. For instance, a child who hates a certain cartoon character will not respond well to therapies that involve that character. Therapists and teachers of children with autism are trained to recognise and adapt to such variations among and within children. Therefore, AR systems for autism therapy must also become capable of such flexibility before they can be autonomous entities in therapeutic interactions. Some systems that identify mental and emotional states have already been proposed, but these are primarily used in various autism treatment procedures (i.e., in the robotics domain).

Also, for an AR system to be successful and achieve a good outcome it should be able to inculcate prosocial behaviours among many users, as identified in our review of the literature. Therefore, it is clear that AR is easily obtainable and can also be obtained by therapists, families, and trainers. When AR for autism has reached the stage when it can be deployed in homes or in a range of different long-term educational and healthcare settings, commercially available AR platforms will facilitate both the evaluation, enhancement and adoption of these specialised AR systems. Moreover, as the number of smart mobile devices continues to grow at an exponential pace, their features and capabilities are also increasing [134-136]. This trend is likely to lead to an increase in usage, and make it easier to build and access AR technology.

We also noted in our review that most studies on AR for autism involved comparatively few users and a short study duration. In the future, we anticipate that studies will focus on larger populations of users and be conducted over a longer time frame.

Also, autism treatment to improve skills has been targeted at enhancing communication, play skills, regulation of emotions and behaviours, self-care issues, and social interaction [137]. However, there is a need for special needs education instructors to collaborate with

AR researchers to create appropriate customised systems to aid children with various needs in general and those with autism in particular [89].

2.10 Machine learning to help diagnose and detect autism

This section reviews the use of machine learning to assist autism diagnosing and prediction. The usefulness of this section lies in its review of clinically diagnostic techniques and early diagnosis that can lead to early interventions and subsequent improvements in the treatment results.

Autism like several medical studies invests and uses machine learning to diagnose or predict diseases and disorders. For example, autism studies used machine learning for prediction (e.g. [1, 138-146]) or diagnosis (e.g. [147-150]). However, some research applied or proposed an improvement available machine learning methodology to enhance the outcomes (e.g. [151]) or reduce the diagnosis time (e.g. [138, 139]), and some research developed a new algorithm (e.g. [142, 149, 152]). Furthermore, several studies investigated the hypotheses (e.g. [1, 140, 145, 153-155]). These studies also concluded that different machine learning mechanisms like classification and clustering are used by a healthcare research centre and organisation to enhance their ability to make decisions regarding child behaviours or health. Also, some studies compared different algorithms (e.g. [141, 143, 144, 147, 156, 157]). Finally, a number of studies focused on different issues, challenges, pitfalls, and promises in relation to applying machine learning in the area of diseases and disorders diagnosis (e.g. [158]).

This chapter divides all studies depending on the data acquisition that has been used by each study into five groups:

A. Movement data (e.g. [1, 140, 146, 159-162]).

B. Eye-tracking data (e.g. [142, 148, 153]).

C. Brain image data (e.g. [143, 144, 151, 152, 155]).

D. Signal data (e.g. [145, 147, 150, 154]).

E. Questionnaires data (e.g. [138, 139, 149, 156, 157, 163]).

2.10.1 Data acquisition

Data acquisition resources that have been used by each study were categorised into five groups: Movements, Eye tracking, Brain images, Signals, and Questionnaires. This chapter displays these data resources in detail.

2.10.1.1 Movement

Many autistic children have atypical movement patterns, such as asymmetric gait or toe walking [164]. The defect of gross motor function in kids with autism is well known to clinicians [165-169] but has not received much experimental documentation, with the exception of repetition but this defect is not among its diagnostic criteria [167-169].

The human motion was divided by a specialist into different levels. Turaga and others divided human motion into "action" and "activity" and these terms are frequently used reciprocally. However, by "actions" we refer to simple motion patterns usually executed by one human and typically lasting for brief durations of time, approximately several seconds. Examples of actions include bending, walking, and swimming. Also, by "activities," we refer to the complex sequence of actions performed by a few persons who associate with each other in a constrained manner. They are commonly described by much longer temporal durations, e.g., two persons shaking hands, a football team scoring a goal [170, 171].

In autism, motion analysis is based on kinematic gait data (e.g. [172]) and upper limb data (e.g. [140]). Autism specific movement signs, which can be obtained before the development of language, are assessed quantitatively [1, 140].

2.10.1.2 Eye-tracking

Eye-tracking is a mechanism that aims to determine the gaze direction of a person's eye in a specific time by eye position at that time, that is moving from one location to another

[173]. Yarbus explained different types of movement for the human eye: fixation, saccades, tremor, drift, pursuit [174].

Autism eye-tracking research differs in social attention measurements and their significance to autism. The bulk of eye-tracking research in autism has employed static images and has concluded that there are differences [175, 176] or no differences [177, 178] between autistic children and typical children while other studies have applied dynamic stimuli and their results are superior to the studies that employed static images for scaling social reply [179].

2.10.1.3 Brain image

Since 1966 the brain anatomy in autistic patients has been tackled in various studies [180], and brain image is one of the most important parts of clinical diagnostic equipment [181]. Although Magnetic Resonance Imaging (MRI) is safe for a child, MRI is performed under general anaesthesia for children. As such, it is not always acceptable to families.

In [182], the findings indicate the prevalence of intensified cortical thickness in ASD particularly, on the left-lateralised side of the brain for children aged six years and above. However, variations in the prevalence of intensified cortical thickness in ASD started to disappear during puberty. However, the risk associated with intensified cortical thickness in ASD is connected to social impact and the connection between cortical abnormalities. The extant research [183] indicated that overall, whether in the brain, the tissue, or the ventricle, the prevalence of intensified cortical thickness in ASD is much larger than typical subjects.

The most recurrent distortions in autism are as follows: intensified total brain, parie-to-temporal lobe, and the volumes of the cerebellar hemisphere. Surprisingly, recent outcomes have indicated that the volume of the amygdala, hippocampus, and corpus callosum could be irregular. Such irregularities inside the neural network probably contain the front-temporoparietal cortex, limbic system, and cerebellum and might constitute the basis of autism. These alterations might arise from irregular brain development during the early years [180].

2.10.1.4 Signal

The Electroencephalogram (EEG) signal (shown in Figure 2.5) specifies the electrical function of the brain [150, 184]. These signals may include helpful information about the braincase. However, it is not easy to extract this information instantly; it needs monitoring and analysis of the signals [184]. Usually, the signals are essentially non-linear and non-stationary [184, 185]. Hence, important features can be extracted for the diagnosis of various diseases using advanced signal processing techniques [184]. The EEG may play an important biomarker sign for autism in the future. But autistic children did not have unusual EEGs in the previous research [145, 186, 187].

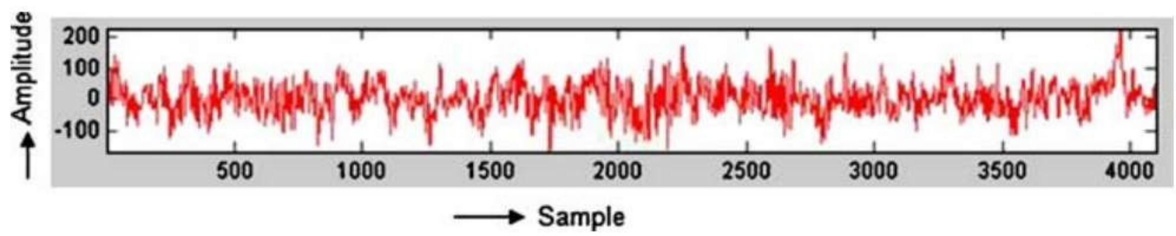


Figure 2.5 Electroencephalogram signal [184].

2.10.1.5 Questionnaires

The questionnaire is the criteria that is most utilised by healthcare professionals and specialists to collect data from autistic children [188]. Usually, parents complete the questionnaires. These contain the kid behaviour checklist (this behaviour includes child sleeping habits), and the repetitive action and compulsive behaviour checklist. The specialist or examiner manages and explains the vocabulary of the questionnaire and monitors the child [189]. However, for parents and clinicians, the questionnaire requires a sizeable time investment [139].

In light of the above, it is difficult to make an early diagnosis of autism by utilising the fixed clinical method. The technicians' diagnosis of autism involves an interview with autistic children that depends on physical appearance. After this, they determine the applicable remedy. Appearance-based determination requires a considerable amount of experienced technicians and it is impossible to estimate. Moreover, there are problems concerning either negligence of parents or the postponement of medical consultations due the parents of a baby not being able to know or predict that their child has autism. In addition, substantive estimation is presently difficult because the finding of estimations differs based on the estimators [190].

2.10.2 Features extraction and selection methods used in autism studies

Feature extraction and selection play a very significant role in the wide area of computer science. The main objective of feature extraction and selection is to get the most useful data from the raw data and produce and minimise dimensionality space [191-194]. In this review, we mention the key algorithms that were used to extract or select features in these studies.

- Backward stepwise selection (e.g. [138]): The algorithm begins by constructing a model that inputs all variables; then, in every round, the algorithm determines the variable that, if removed, will enhance the performance [195].
- Hill-climbing feature selection (e.g. [140]): The heuristic techniques utilise a greedy method to choose features [196] based on the importance of the feature. The hill-climbing algorithms select the features, as heuristics hill-climbing approaches often output a non-minimal feature combination. However, there is no guarantee for optimal output for this algorithm [196, 197].
- Fisher's discriminant ratio (e.g. [1]): an active features selection algorithm [198], It is used to decrease the dimension based on statistical pattern recognition [199].

The algorithm is described as follows: suppose the target is to find a line in the original space such that the projective points on the line of the sample points can be divided as much as possible by some point on the line and there are pair types of sample points in n-dimension data space [198, 199].

- Forward-feature selection (e.g. [149]): it is one of key methods that is used to select features. The accuracy of a model is tested based on the incremented feature subset. Then the feature that gives the highest accuracy is chosen. The procedure stops when no more features enhance the results, or the number of features equals the predefined size [200].
- Linear Discriminant Analysis (LDA): (e.g. [2, 3]) LDA is utilised for data categorisation and dimension reduction [201].
- Histogram of oriented gradient feature (e.g. [146]): Histograms of Oriented Gradients (HOGs) are commonly used in computer vision, for example, pedestrian recognition based on an image represents invariant to 2D rotation [202].

2.10.3 Classification algorithms that have been used in autism studies

There are many classification algorithms that have been used in autism studies among them are:

- ADTree (e.g. [139]): ADTree has many cases, for example voted decision stumps, voted decision, and decision trees. Each tree has many paths. When the sample reaches a decision node it goes to the next decision node until it reaches the leaf or node that agrees with the result of the sample [203].
- LMT (Logistic Model Trees) (e.g. [139]). It combines decision tree and logistic regression [204].
- Support Vector Machine (SVM) (e.g. [1]). The SVM is a supervised learning

technique. This means that it is taught by providing it with examples of the mappings between labels and objects. The SVM can be used for both classification and regression [205, 206].

- Linear Discriminant Analysis (LDA) (e.g. [147, 156]) LDA is utilised for data categorisation and dimension reduction [201].
- Nearest neighbour classifiers (e.g. [145, 150]): Nearest neighbour classification is a mechanism for dividing datasets into several classes. The group of a new object is determined by the labels of the most similar already existing objects. To optimise the mechanism for a certain dataset, a different number of the nearest neighbour to evaluate can be chosen. The mechanism can be improved by weighting the effect of the nearest neighbours based on their distances. Using a distance function other than regular Euclidean distance, the method can be expanded to operate on datasets with symbolic attributes. One of the strengths of the mechanism is that it is intuitive to understand and easy to implement, and compared to other object classification mechanisms it executes well, although it can become quite computationally demanding when operating on large datasets. Nearest neighbour classifiers can be used in medicine to automate the diagnosis process [207].
- NBTree (e.g. [139]): It combines both the decision-tree classier and the NaiveBayes classifier. The nodes of the decision-tree include univariate splits as regular decision-trees and the leaves hold Naive-Bayesian classifier. It represents the learned knowledge in the form of a tree which is constructed recursively [208, 209].
- The logistic regression model (e.g. [139]). It is also known as logit and is the statistical model for analysing a dataset in which there are one or more independent variables that define a result [210-212]. This classifier is commonly used in disease data for classification, prediction, and regression [211, 212].

- LIBSVM (e.g. [139]): it is a library for the Support Vector Machines. This package was developed in 2000 to assist researchers to simply the use of SVM with their applications [213].
- Naïve-Bayes (e.g. [139, 145]): It is the least difficult of these models because it handles all the attributes of the instance independently of each other, although most of the time it works very well [214].
- Random forests (e.g. [139, 156, 163]): Random forests are proposed for building a group containing the predictor and a collection of decision trees with chosen subspaces of data. Despite increasing attention and applied utility, there has been insufficient work done in terms of statistical features and the algorithm's equations [215].
- Radial basis function(e.g. [143]): In many studies of signal processing, the radial basis function network represents a good alternative to the neural network with two layers. It is based on initial data points that were selected randomly as radial basis function centres, then for solving weights of the network they utilise singular value decomposition. Accordingly, a random choosing of centres is considered one of the main disadvantages of this function [216].

2.11 Conclusion

This chapter aimed to explore the essential characteristics of AR systems that help in diagnosing and treating autistic children. In addition, it clarified the design criteria for the AR system and the challenges associated with this type of system by conducting a review of related works. Based on this review, we will build an AR system as a case study that included design decisions and considered the appearance aspects of the design. Based on our evaluations, we hope that our proposed design can accommodate most of the criteria required for designing an effective AR system for autism.

Moreover, this chapter makes a significant contribution to this area of research for several reasons. First, the study combines all the steps necessary to develop an automatic diagnostic system for the detection and classification of autism. Second, it provides knowledge that helps researchers assess the importance of data type, extract high-level parameters, and define them, and provide appropriate classification based on the type of data.

Although some studies are very accurate, they often employ uncomfortable or unacceptable environments for children and their families. For example, obtaining brain signals and images requires subjecting the child to general anaesthesia (GA). Therefore, the next chapter will take into account the environment and the degree of acceptance from all parties when building a new augmented reality system.

Finally, there are no computers that can replace the intuition of a healthcare professional. However, studies on design features and analysis procedures may lead to a good model (both child-friendly and inexpensive) that simultaneously helps families improve the early diagnosis of their autistic children and achieves our goal of the early detection of autism in children and early intervention that leads to good long term results.

To conclude, we have sought in this chapter to take advantage of previous studies wherever possible, and we have involved caregivers and psychology experts in building a new effective and child-friendly AR system. This system will be explored in more detail in the next chapter.

Chapter Three

The New Augmented Reality System

(The content of this chapter has been published in *Multimedia Tools and Applications Journal*)

This chapter focuses on our new AR system as a case study. It covers the design standards and decisions as well as the key features and appearance of the system. The chapter concludes by making some recommendations for the further development of an AR system for application in the domain of child autism. This study compared fifteen school autistic children aged (48-60 months) with fifteen non-autistic children, different classifiers were able to successfully classify participants.

3.1 Introduction

A diagnosis of ASD at the beginning of a child's life is the main way in which to improve the likelihood of a better treatment outcome. Researchers around the world are searching for new symptoms and signs that will help to reach an early diagnosis. The early diagnosis of ASD is the key to early intervention as it is early interventions that produce good treatment outcomes. Upper limb movements are one of the signs that show promise in terms of the early identification of ASD. In this part of the chapter, we therefore show how we aim to develop a method to diagnose autism in children by measuring their upper limb movements.

In our proposed method we use AR to create a virtual object in order to encourage the children to move their hands. The system records all the children's movements by using the Microsoft Kinect sensor, which is potentially a low-cost solution. Thus, the key two components of the system are an AR game and a program to record movements. The new system provides a customisable platform for autistic children which includes a game designed in such a way that it can be controlled by a child's hand movements. To create this system, the latest developments in HCI are utilised, and the kinematic data is recorded using Microsoft Kinect and then analysed. Also, in order to encourage the child to interact with the new system, the system employs AR to design a virtual object and register the movements in a child-friendly environment, which is a cheap and effective approach. The data analysis step is performed by using a support vector machine (SVM) and an extreme learning machine (ELM) in order to reach an early diagnosis of autism.

The next part of the chapter summarises the techniques that have been used in previous studies for the measurement of the upper limb movements of autistic children and addresses the challenges encountered in the design and implementation of these techniques. Then it introduces the AR system design and implements the proposed technique to measure the upper limb movements of autistic children based on the ability of Microsoft Kinect to represent human joints using 3D coordinates (see Figure 3.1). The chapter then outlines some future recommendations for the further development of the program.

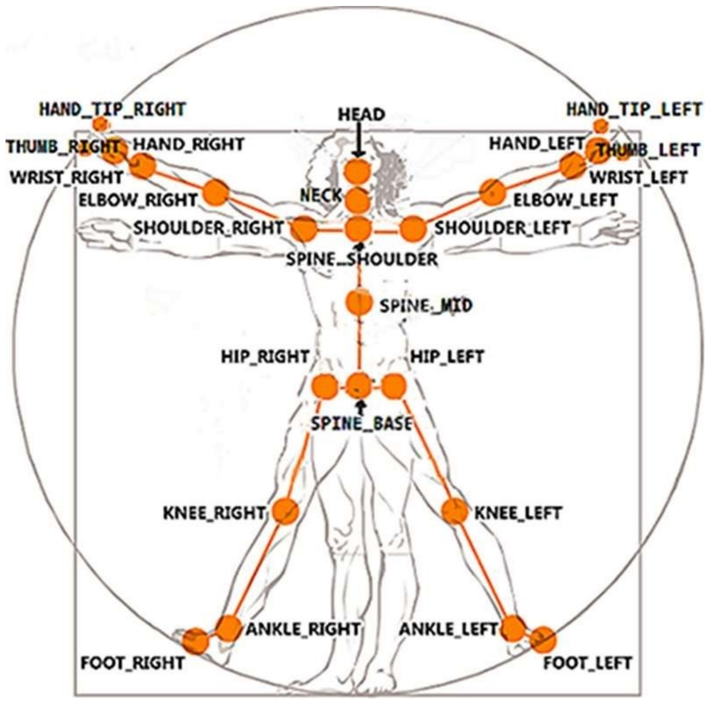


Figure 3.1 Names of the joints in the human body used by Microsoft Kinect [217].

3.2 Upper limb measurement system for autistic children

In [218], autistic students were recruited as the study participants. Specifically, the participants were three autistic students aged between eight and ten years old attending a special education class. Data on upper limb movement were collected by observation. A monitoring chart was produced that included data on physiological observations, arm coordination, racing time, tempo/arrangement, and game rendering. The researcher monitored and recorded the relevant data during the time that the participant played the game. The method used to take the measurements is illustrated in Figure 3.2. It should be noted that this method is considered to be inaccurate because it measures upper limb movements by observation only.

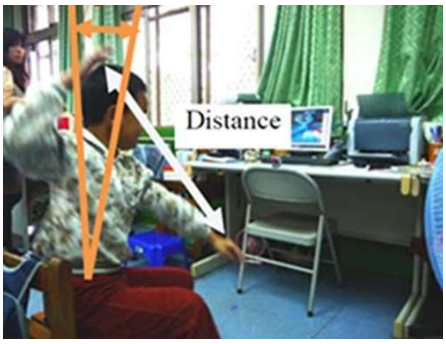


Figure 3.2 Measuring the upper limb movements of autistic children by observation [218].

In [1], an optoelectronic system was used to obtain 3D kinematics data. The data were gathered by using eight infrared-movement analysis cameras at 60 Hz that were positioned four per aspect at a distance of 250 centimetres from the children. Passive markers (1 cm^2) were connected to the ulnar and radial surfaces of the children's wrists and to the hand dorsum on the fourth and fifth metacarpals (see Figure 3.3). Furthermore, two markers were set on the ball and four on the rim of the container below the target zone. The responses of 15 participants with autism across a range of ages were compared with those of 15 TD participants. The ASD and TD participants were matched to each other according to mental age. Each child participated in ten trials: five consecutive trials on the left hand and five on the right hand. However, the experiment was interrupted so that the participants could rest. The drawback of this type of method is the high cost, limited availability, and poor transportability of the tool.

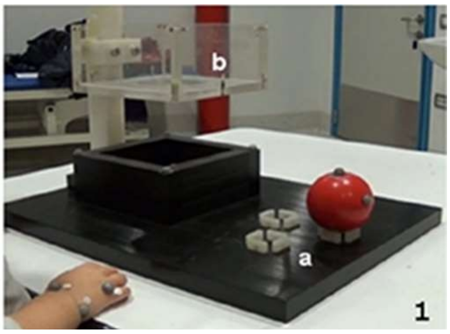


Figure 3.3 Markers appear on the child's wrist [1].

In [219], the researchers were initially present with the participant and asked her/him to put on the magneto-inertial sensor (a coloured bracelet positioned at the wrist). Then, the experiment commenced. At the beginning of every trial, the researcher demonstrated the task to the child while she/he was seated in front of a desk (see Figure 3.4). Participants were encouraged to extend their arms by beginning with their arms in the same position and setting their palms on two animal stickers positioned on the table. Twelve children aged between three and four years old were involved in testing this proposed approach: six were at high risk of autism and six were at low risk. However, in this study, the results of various trials were excluded from the analysis if the participants' fingers motions were not suitable for use or there was equipment failure.

By and large, the previous studies have developed high-cost, complex systems such as a gaze-monitoring device, a stereo-photogrammetric movement evaluation system, and force measurements in very structured laboratory environments. However, these systems are not really viable for the diagnosis of ASD in a variety of children in a range of real-world settings due to the excessive cost, restricted availability, and bad transportability of these tools [219].

Figure 3.4 Sensors appear on the child's wrist [219].

Our proposed approach differs from previous studies because it uses a technique that involves a camera and the analysis of user movements based on joint coordinate locations (X, Y, Z). Also, the new system employs AR to design a child-friendly environment without any tension that is related to child movements to help families and specialists to diagnose autism. Moreover, the new system does not use wearable hardware sensors or markers because the lack of such apparatus makes the system more widely applicable and comfortable. Our aim is to encourage a child to interact freely with the computer graphics of the AR system, so that the system can accurately track and register the specific details of the child's upper limb movements. Also, the new system is low-cost and movable and there is no need for any sensors to be stuck onto the body. Thus, it has several advantages over the above-mentioned systems which are either marker-based or/and wearable sensor-based systems.

3.3 Method

This section describes the system requirements for the hardware and software, the system equations as well as the system description, system design, and system implementation of our new AR diagnostic technique. It also discusses the expert feedback and the pilot study that were obtained for the new system.

3.3.1 System requirements

A system runs efficiently when all system hardware requirements and system software requirements are available. The new system needed the following hardware components and software resources.

- Hardware: Kinect is a Microsoft product that is used as a motion-sensing input tool. It can be employed on different platforms, including Windows, Xbox 360 and Xbox One [220]. Kinect is used for detecting the motions and gestures of humans and it enables interaction with software systems or games without the need to use a controller. We used Kinect for Xbox One for our new system. Kinect for Xbox One was produced in 2013 and is considered the final form of the Kinect sensor in the Kinect series at the time of writing this chapter. Kinect looks like a straight bar webcam and it is composed of three main parts: a RGB camera, depth sensor, and multi-array microphone. Its features and specifications are shown in Table 3.1. The sensor provides 3D motion capture, facial recognition and voice recognition. The Kinect v2 sensor means Kinect for Xbox One and Kinect for Windows version 2, while Kinect version 1 sensor means Kinect for Xbox 369 and Kinect for Windows version.

Table 3.1: Basic specification for Kinect v2 [220].

Specification	Value (Range)
Colour Camera	1920 x 1080 @30fps
Depth Camera	512 x 424
Depth Distance	500mm ~ 8000mm
Horizontal Field of View	70 degrees
Vertical Field of View	60 degrees
Full Skeleton Tracked	6
Skeleton Joints Defined	25 joints/player

- Software: The AR game for the new system was built by using Unity software. Unity is cross-platform software that was initially created for developing games but is now used in a wide range of domains, such as architecture, art, children's apps, information management, education, entertainment, marketing, medical and military applications, physical installations, simulations, training. Unity takes on a lot of the complexities of developing games and similar interactive experiences and looks after them behind the scenes. Consequently, people can concentrate on designing and developing their games. These complexities include graphics rendering, world physics and compiling together. More advanced users can interact and adapt these aspects when required, but less advanced users do not need to concern themselves with them. Games in Unity are developed in two stages. The first involves the use of the Unity editor and the second involves the use of code, specifically C#. Unity is bundled with MonoDevelop or Visual Studio 2015 Community for writing C#. The tracking part of the software is self-written software in C# which is built by using Visual Studio 2015. C# is an object-oriented language and it is also a multi-paradigm programming language due to its robust declarative, generic, functional, and imperative commands [221].

3.3.2 System equations

In our new system, Kinect was used to capture 3D movement patterns, based on the concept of each joint being represented as a point in three coordinates, as shown in Figure 3.5.

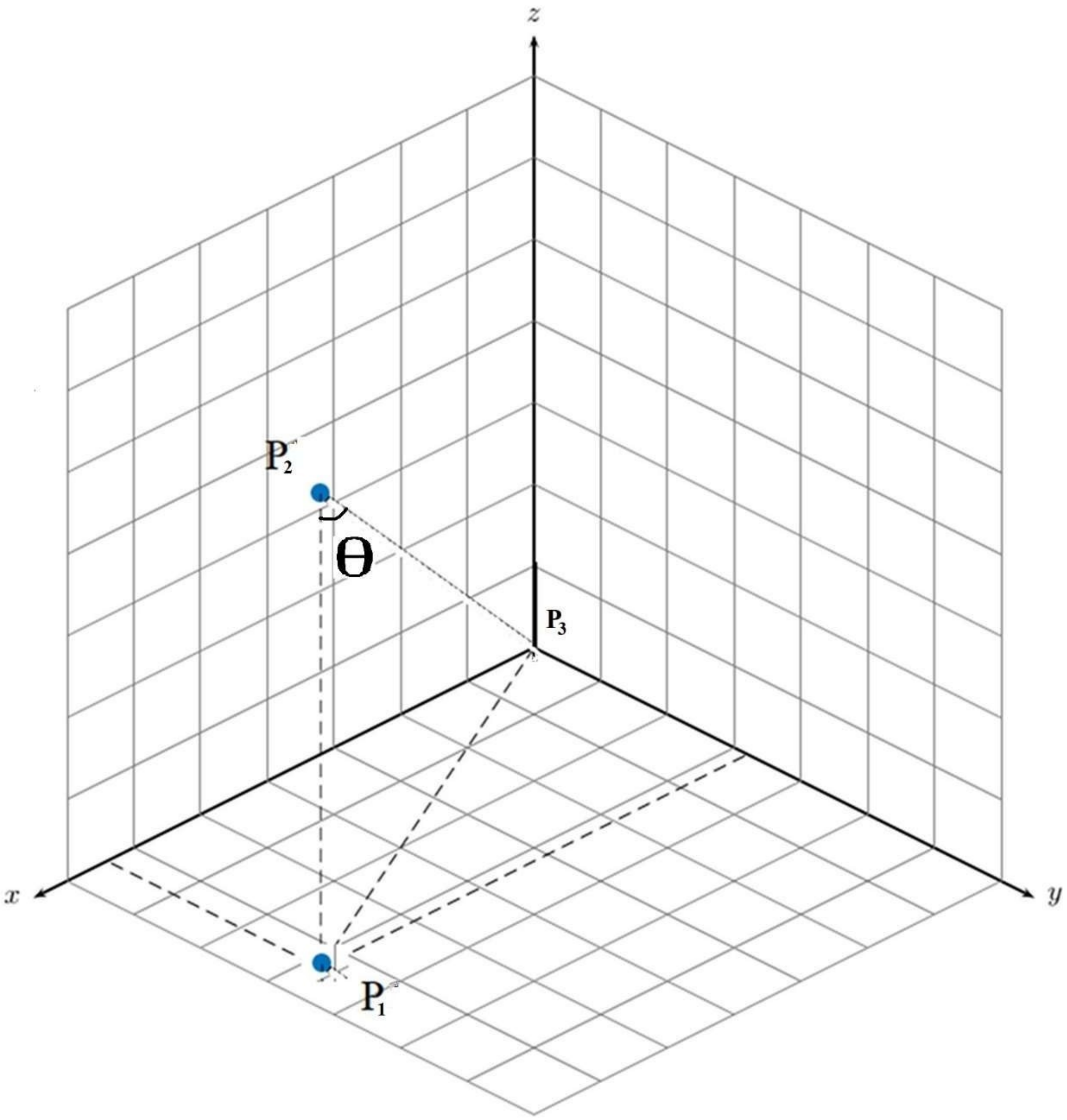


Figure 3.5 Three coordinates.

P_1, P_2, and P_3 represent the locations of human joints:

$P_1 = (X_1, Y_1, Z_1)$.

$P_2 = (X_2, Y_2, Z_2)$.

$P_3 = (X_3, Y_3, Z_3)$.

The distance (D) between the old location P_1 for a specific joint and the new location P_2 for that joint is represented as follows:

$$D = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2 + (Z_2 - Z_1)^2} \quad (3.1)$$

The speed (S) of the specific joint between two locations in a particular time (T) is calculated by (the average speed is considered):

$$S = \frac{D}{T} \tag{3.2}$$

The formula for angle given by three *3D* coordinates is as follows:

The angle (θ) between three different joints P_1, P_2, and $P3$, (shown in Figure 3.6) is calculated as follows:

$$\overrightarrow{P_1P_2} \quad = \quad OP_2 - OP_1 \tag{3.3}$$

$$\overrightarrow{P_2P_3} \quad = \quad OP_3 - OP_2 \tag{3.4}$$

Where O is the origin of the axes.

$$\overrightarrow{P_2P_1} \cdot \overrightarrow{P_2P_3} = \overline{P_2P_1} \quad \overline{P_2P_3} \cos\theta \tag{3.5}$$

Where "." as the scalar product.

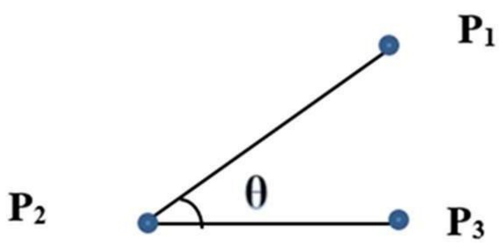


Figure 3.6 Joint angle θ between two joints.

By rearranging the equation, the equation becomes

$$\theta = arccos\left(\frac{\overrightarrow{P_2P_1}.\overrightarrow{P_2P_3}}{\overline{P_2P_1} \quad \overline{P_2P_3}}\right) \tag{3.6}$$

3.3.3 System description

In this section, we describe the AR and tracking components of the new system.

- Augmented reality: Augmented reality is a beneficial and ideal interface tool for enhancing the capabilities of children with autism because AR can support interactive and attractive interfaces that can be accessed by using the hand or a gesture without utilising standard peripherals such as a mouse and keyboard [100, 105]. This characteristic of AR promotes interaction between the child and the object while raising their interest and curiosity in the task or activity [100, 222]. Augmented reality has many capabilities that can help a child with autism because it supports visual conceptualisation by superimposing virtual contents onto the real world with which children with autism are familiar [89, 90]. As such, AR technologies may offer an expanded and alternative option for diagnosis and treatment that can go beyond professional therapeutic contexts, allowing family members and TD peers to be actively engaged as well [90]. Also, the game task is easy and enjoyable enough to ensure the full encouragement and compliance of all children during the game. The game consists of a virtual ball and tube, and the child is asked to insert the virtual ball into the tube (see Figure 3.7). We deliberately chose a simple task of inserting a ball into a clear tube that is open at both ends because it is the most discriminating task compared to many different tasks [6].

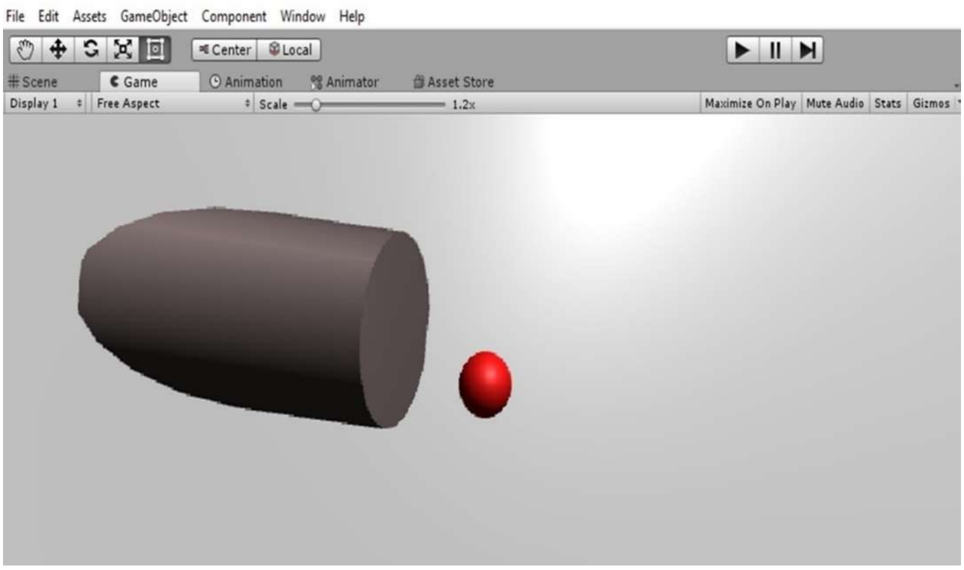


Figure 3.7 The AR game in the new system.

Tracking: The command "Create Virtual Object" is activated when the marker (stimulator) is recognised by the system. The system then calculates the true position of the stimulator accurately and generates a virtual object (ball) and embeds it in real time into the real environment in front of the stimulator [223]. The system is based on tracking joints without concern about the children's physical characteristics weight, height, gender, face, etc. Also, the system then tracks and records the child's movements. The tracking procedure involves a filtering process, which is followed by a motion feature extraction procedure. The Kinect sensor is located 2.7 metres away from the user at a height of 1.2 metres above the floor. This experimental setup is a reference point for experimental for both ASD and TP children. The experimental setup impacts the accuracy of the measurement. For example, the Kinect location should allow recognizing the child's body and it impossible happens if Kinect is located 1.0 meters away from the user. During the game, the body of the user should face the Kinect sensor. The user must face the sensor to prevent the arm joints from intersecting with the body joints, as shown in Figure 3.8. This setup generates a reliable hand motion for assessing the impact of each joint of the arm on the overall speed of the right-hand movement more precisely. The data collected on hand movements in experiments conducted among several study participants can be used as a benchmark for the effective detection of the speed of a hand movement.

Figure 3.8 The arm joints are prevented from intersecting with the body joints in the new system.

3.3.4 System design

As mentioned above, the AR system was designed based on a simple game interface, as shown in Figure 3.9. We chose the simple task of inserting a ball into a clear tube open at both ends because it is the most discriminating task compared to many different tasks [6]. The system generates a virtual ball and tube in different colours to encourage the child to interact with the system. To enhance interaction with the system, further visual and sound stimuli are added to the scene.

Figure 3.9 Fitting the ball into the tube [224].

The tracking technique was based on joint coordinate locations (*X, Y, Z*), which are in turn based on the concept of each joint being represented as a point in three coordinates. The tracking part was self-written software that depended on 3D space equations.

3.3.5 System implementation

The new system used a marker-less AR technique, which means that there were no intrusive ambient markers that were not part of the environment [225]. The AR part was created by using the Unity platform, and marker-less tracking was used as the tracking platform.

The scene contained two objects: a ball and a tube. The system created a virtual ball, and when the system recognised the child's hand, it started to register the child's movements and details until the child inserted the ball into the tube or a specific task end-time was reached.

The proposed technique utilised a Kinect and analysed user movements based on joint coordinate locations (*X, Y, Z*). Kinect was used to capture 3D movement patterns, based on the concept of each joint being represented as a point in three coordinates. The tracking part was self-written software in C# built by using Visual Studio 2015.

3.3.6 Expert feedback and pilot study

We discussed the system model with three psychology experts and received a lot of valuable feedback. A pilot study was also conducted to test the new system. It involved two TD children who were between three and eight years old and who could interact and deal successfully with the system. Several improvements were made to the system design based on the positive feedback received from the psychology experts and our observations during the pilot study.

3.3.7 Experiment

This section describes the experiment participants, the system procedure, the methods applied for data collection, the experiment task, and the analysis procedure which included a feature extraction and classification algorithm. This section also describes how the performance of the system was evaluated.

3.3.8 Participants

The system was tested to determine whether it could accurately discriminate 15 children with autism from 15 TD children, on doing so, we used kinematic analysis to assess the children's performance of a simple task in the AR system environment. The data was collected after we gained the ethical approval number ETH18-2710 approved by the University of Technology Sydney, titled "Implementation of an Augmented Reality Game to Track Upper Limb Movement in Autistic Children".

3.3.9 Procedure

In the experiment, the new AR system followed the procedure outlined below:

- The system creates a virtual ball and tube.
- The child is asked to insert the virtual ball into the tube.

- The system calculates the angles between the different joints and the speed of the movements.
- After the task is completed, the system generates a text file that contains the movement measurements (see Table 3.2).

The following system steps and forms need to be completed to set the parameters for the experiment:

- The first step involves filling in the form for the system settings (see Figure 3.10).

In this step, the researcher chooses the angles they wish to consider in the experiment. The researcher can select from one to six angles. If one angle is selected, the first field is filled for the first angle and the fields for the other five angles remain empty. If two to six angles are selected, the measurements for all the joints are listed in the combo box (see Figure 3.11).

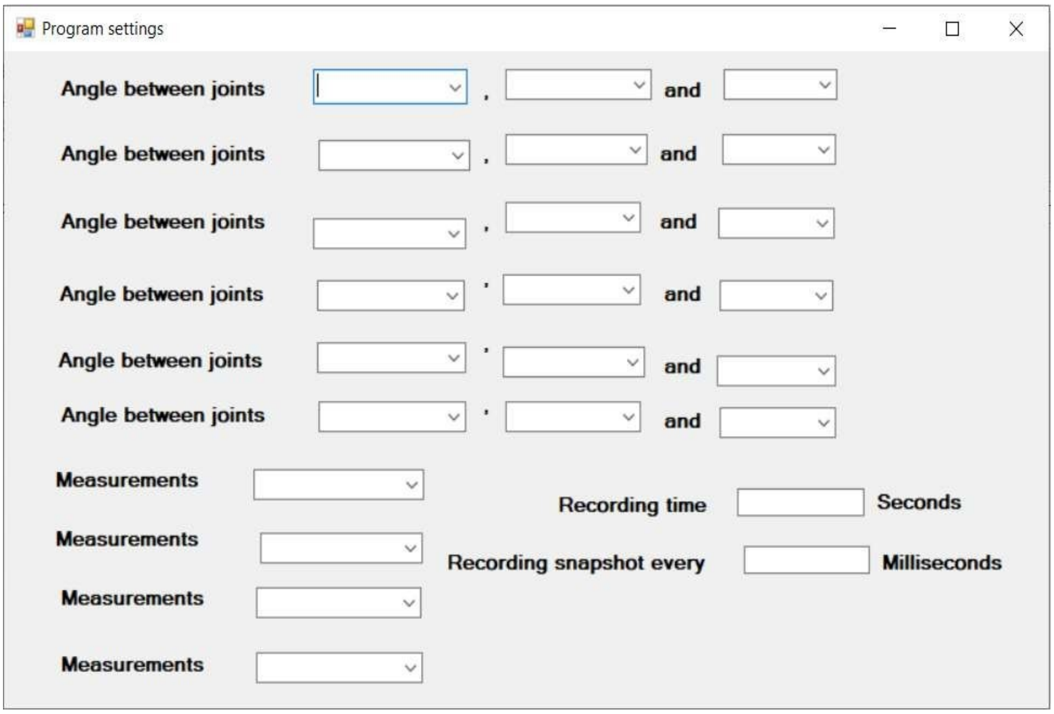


Figure 3.10 New system settings.

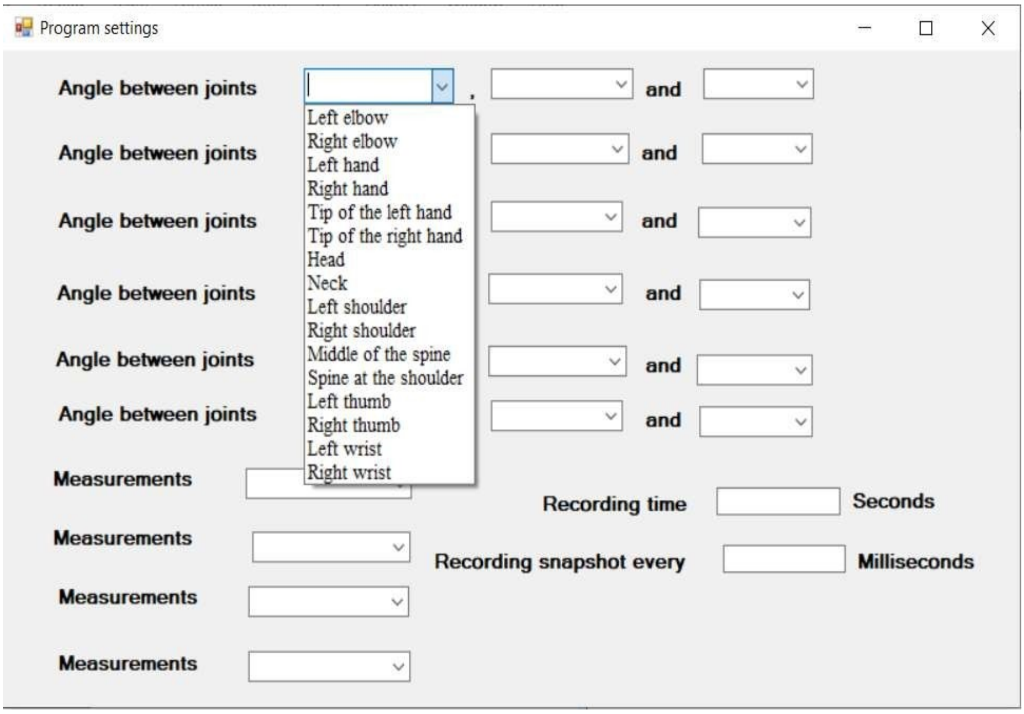


Figure 3.11 Upper limb joint names in the new system.

- The second step involves filling in a form to select the joint or joints of interest (see Figure 3.12) in this step, the researcher can decide to assess from one to four joints and selects the joints by filling in the relevant fields in the form.

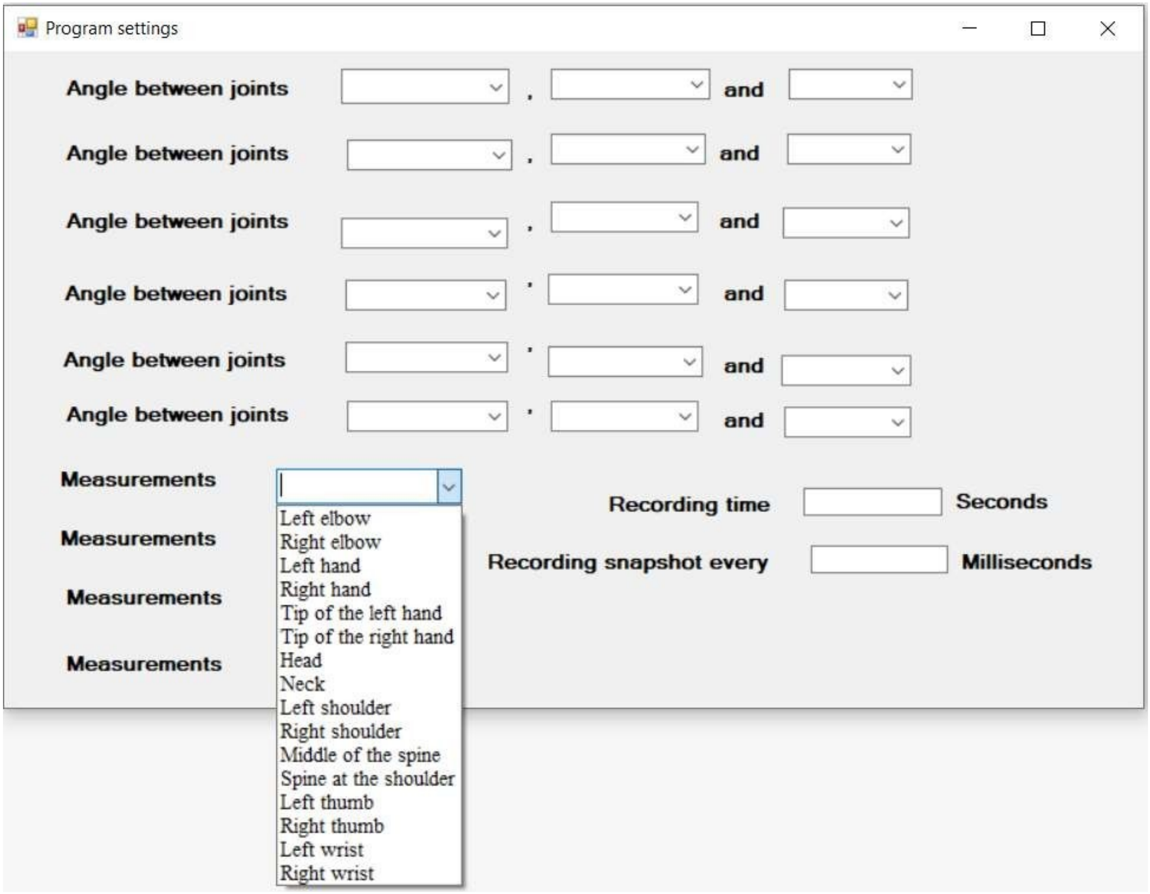


Figure 3.12 Upper limb joint names for computing the measurements in the new system.

- The third step concerns setting the experiment duration in seconds (see Figure 3.13).
- The fourth and final step requires the researcher to determine when a snapshot of the child performing the task should be recorded (see Figure 3.13), In other words, the researcher has to set the frequency-time at which the system writes the measurements in the text file.

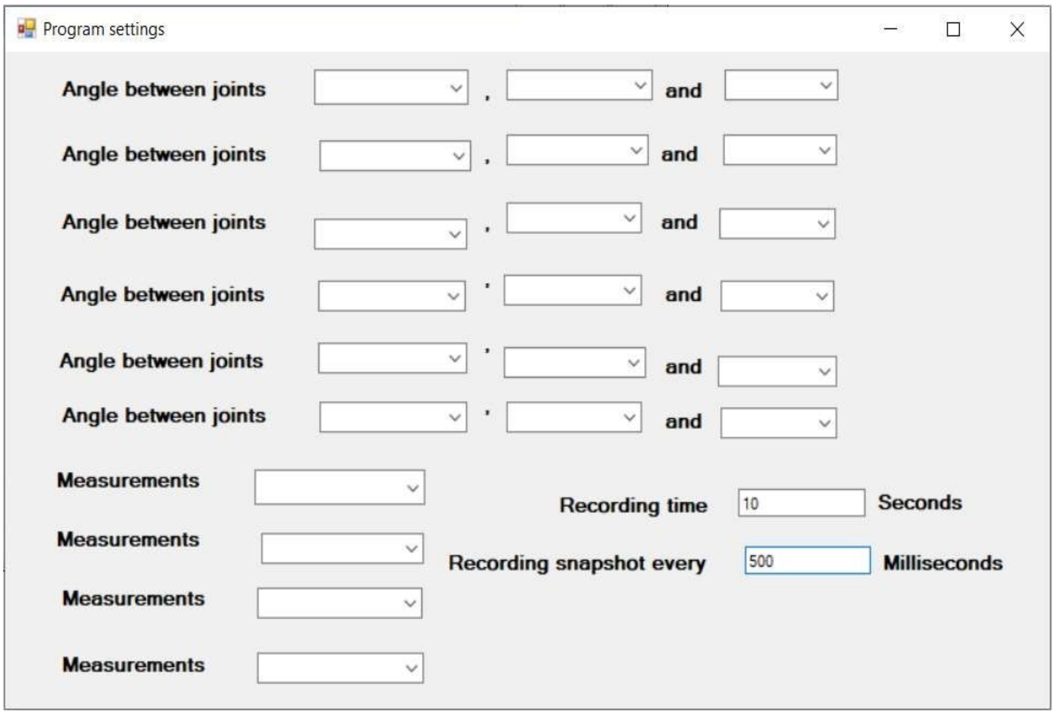


Figure 3.13 Recording time and a snapshot time in the new system.

Table 3.2 : Kinematic data sub-movements that were used in this study.

Sub-movement	Description
Reach duration	The time interval between the start of playing movement and the contact with the object.
Place duration	The time interval between the instant in which the object has touched and the instant in which it is released into the target.
Latency reach place	The time interval between the end of the reaching phase and the beginning of the placement phase.
Velocity 1	The velocity of the thumb joint between the start of playing and the contact with the object.
Velocity 2	The velocity of the thumb joint between the instant in which the object has touched and the instant in which it is released into the target.
Wrist angle 1	Angle between the thumb joint and the elbow joint at the movement reaching the ball.
Elbow angle 1	Angle between the wrist joint and the shoulder joint at the movement reaching the ball.
Shoulder angle 1	Angle between the elbow joint and the spine-shoulder joint at the movement reaching the ball.
Wrist angle 2	Angle between the thumb joint and the elbow joint at the movement placement of the ball.

Elbow angle 2	The angle between the wrist joint and the shoulder joint at the movement placement of the ball.
Shoulder angle 2	The angle between the elbow joint and the spine-shoulder joint at the movement placement of the ball.
Hand	Hand used (left or right).

3.3.10 The AR system evaluation

To evaluate the effectiveness of the new AR system in terms of HCI, caregivers took part in a post-intervention structured interview to assess the feasibility and functionality of the application. The application was felt to have both high tolerability and engagement. Caregivers also felt that all children found the system enjoyable and fun to use. Table 3.3 illustrates the AR system evaluation provided by the caregivers, from which we can see that it has the advantages of being friendly and easy to use.

The interactive computer software is usually evaluated by several criteria [226-228]. Therefore, the child's caregiver was asked to evaluate the new system by a 1–10 scale of satisfaction: ten means very satisfied, and one means very dissatisfied. Four caregivers were considered (two for the autistic children group (15 children) and two for the typical children group (15 children)). From the table below we can see that the software has the advantages of being friendly and easy to use.

Table 3.3: Caregivers' assessment of the new AR application for TD and ASD children.

Criteria	First caregiver (TD)	Second caregiver (TD)	First caregiver (ASD)	Second caregiver (ASD)
Level of engagement with the application	10	9	9	10
• The system can be used frequently.	9	9	10	9
• Children learned to use the system very quickly.	10	10	8	8
• The system is recommended by trainers.	10	9	10	10
Level of tolerability	10	10	10	9
• Safety	10	10	10	9
• Child-friendly	9	10	9	8
Level of enjoyment	9	9	8	9
• The children performed a task that could be completed.	10	10	9	8
• The children were able to concentrate on what they were doing.	9	9	8	9
• The concentration was possible because the task had clear goals.	8	8	8	7
• The design of the system is visually appealing.	10	9	10	10
Ease of use	10	10	9	9
• The system is easy to use.	10	10	9	10
• The child does not need the support of a technical person to be able to use the system.	9	9	8	8
• The system is not cumbersome to use.	10	10	10	10
• The child felt very confident using the system.	10	9	9	8
• Before the child used the system, he/she did not need to learn a lot of new things.	10	10	10	10
Level of interaction with the application	9	9	9	10
• The children liked exploring the system.	10	10	10	10
• The system is easy to reset.	8	7	8	8
• The children did not mind making mistakes.	9	9	10	10

• The children liked the game and repetition.	10	10	9	10
• The system motivated the children to play.	10	9	9	9
• The behaviour of the virtual object is equivalent to the system behaviour in the physical paradigm.	9	9	9	10
Valuable	9	10	10	10
• The game has a worthy goal.	9	10	10	10
• The system helped to enhance the skills of the children.	9	10	10	9
Efficiency	9	10	10	10
• The children did not wait for a system response to continue the task.	9	10	10	10
Consistency	10	10	9	9
• Objects in the system interacted in a smooth way.	9	9	8	10
• The children knew the types of actions that were available based on the reactions of the system.	10	10	9	8
• The virtual object visible to a child was compliant with the real world's physical model.	9	9	8	9

3.3.11 Tracking system validation

A lot of papers [229, 230] have tested and validated the accuracy of Kinect, and they have found that the accuracy of Kinect V2 landmark movements was moderate to excellent and depended on movement dimension, landmark location and the performed task. Also, most of the derived clinical parameters showed ‘good to excellent absolute’. Therefore, Kinect V2 has the potential to be used as a reliable and valid clinical measurement tool. Since the measurements are valid, we employed these measurements in our system to calculate the joint angles and speed by using the common equations and taking into consideration the recommendations made in previous studies regarding the use of Kinect

V2. Therefore, to validate our use of these measurements we compared them to the traditional method based on image and video measurements (e.g. [218]), and found that the accuracy was ‘excellent absolute’.

3.3.12 Data collection

As mentioned above, the snapshot recording time determines the frequency-time that the system writes the movement measurements in the text file. After the experiment has finished, the system generates a text file that contains every measurement captured during the experiment.

3.3.13 Data analysis

This section clarifies how the kinematic data is treated and discusses the motion feature extraction method, the classification algorithm, the performance of the classification algorithm, and the method of performance evaluation.

3.3.13.1 Feature extraction

The features that were extracted from the collected raw sub-movement measurements were more discriminative for the children with autism (ASD) than for the TD children. Feature extraction was executed by using Linear Discriminant Analysis (LDA). Usually, LDA is utilised for data categorisation and dimension reduction [201]. In this study, we applied LDA for dimension reduction only.

All the mentioned goals can be done by detecting the projection hyperplane which reduces the variance in the interior of the classes and increases the space between the classes (see Figure 3.14). This hyperplane can be employed for many functions, including categorisation, dimension reduction and determining the degree of discrimination among the features [231]. “The intuition behind LDA. Data samples in two dimensions are projected in a lower dimension space (line). The line has to be chosen so that the projection maximizes the “separability” of the projected samples” [231].

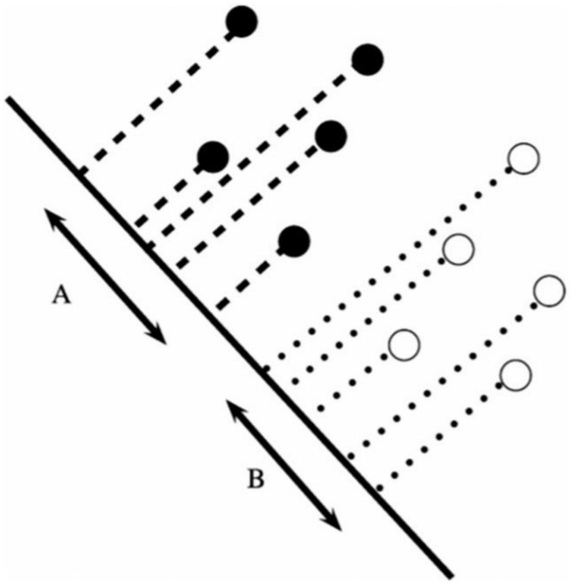


Figure 3.14 The line has increased the space between the two classes [231].

The LDA degree is computed with base-technique using LDA, for a selected model *x* and a specified discriminant function *g(x)*. In this situation, LDA determined. A linear discriminant function collecting of the variables of *x* can be written as follows [232, 233].

$$g(x) = w^{T} * x + w_0 \tag{3.7}$$

Where *w* is the weight vector and w_0 is the threshold weight.

"T" stands for the transpose operator.

The weight vector is calculated by

$$\mathrm{w} = \Sigma_C^{-1}(\mu_2 - \mu_1) \tag{3.8}$$

Where μ_i is the average value of class *i* from *C* classes.

Σ_C^{-1} is the common covariance matrix for class C.

The covariance matrix (cov) and the average (μ) for a small sample are computed as follows:

$$cov = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)\,(x_i - \mu)^T \tag{3.9}$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.10}$$

The study used LDA in the pre-processing step for the raw data in the Table 3.2 to reduce dimensionality to two dimensions, and reduced the variance in the interior of the classes and increased the space between the classes.

3.3.13.2 Classification algorithm

The classification of the ASD and TD participants was performed by employing two classification techniques, namely the SVM and the ELM. The SVM classifier is a common classifier and an easily separable algorithm. On the other hand, the ELM is a relatively recent classifier, and we used this classifier to see if it would improve the results. In this study, the Matlab platform (Matlab version R2017a) was used to implement the two classifiers. In addition, the study utilised the functions of the Matlab toolbox to achieve this task.

The SVM is a supervised learning technique. This means that it is taught by providing it with examples of the mappings between labels and objects. The SVM can be used for both classification and regression [205, 206]. The functions that describe the SVM for binary classification can be written as follows [234, 235]:

The training data form is:

$$\{x_i, y_i\} \quad where\ i = 1 \dots .L, \quad y_i \in \{-1,1\}, x \in \mathbb{R}^D \qquad (3.11)$$

L is the number of training points.

x_i is an item or training point number (i).

D means dimensional (number of attributes).

y_i is the class for training point number (i); Here we have two classes. So, y_i value = -1 or 1.

D = 2 will be a plan and D > 2 is a hyperplane.

The hyperplane is described via $w.x + b = 0$.

w is normal (vertical) to the hyperplane.

$\frac{b}{\|w\|}$ is the vertical length from the hyperplane to the origin.

Referring to the graph in Figure 3.15, the SVM aims to select w and b, thus the training data can be written as follows:

$$w.x_i + b \geq +1 \quad for\ y_i = +1 \tag{3.12}$$
$$w.x_i + b \leq -1 \quad for\ y_i = -1 \tag{3.13}$$

Where "." as the inner product.

Then these two equations combine in Equation (3.14).

$$y_i\ (x_i\ .w + b) - 1 \geq 0\ \forall_i \tag{3.14}$$

H_1 and H_2 are the two vectors that contain the points closest to the separating hyperplane. These vectors are support vectors.

The planes H_1 and H_2 can be written as:

$$\begin{aligned} x_i\ .w + \mathrm{b} &= +1 \ \text{ for } H_1 \\ x_i\ .w + \mathrm{b} &= -1 \ \text{ for } H_2 \end{aligned} \tag{3.15}$$

Returning to Figure 3.15 where d_1 and d_2 are the distance between H_1 and the hyperplane, and between H_2 and the hyperplane, respectively.

Also, $d_1 = d_2$ is called the SVM's margin.

The Margin = $\frac{1}{\|w\|}$ Therefore, maximising the margin is meant to reduce the $\|w\|$.

Therefore, the required equation is

$$\min\|w\|\ such\ that\ y_i(x_i.w + b) - 1 \geq 0\ \ \forall_i \tag{3.16}$$

To apply quadratic programming (optimisation process), we used the expression of minimising the min$\frac{1}{2}\ \|w\|^2$ instead of minimising $\|w\|$. So, the new form of the required equation is

$$\min \frac{1}{2} \|w\|^2 \; such\ that\ y_i(x_i.w + b) - 1 \geq 0 \;\; \forall_i \tag{3.17}$$

To consider the constraints in this minimisation, the Lagrange multipliers were applied α, $where\ \alpha_i \geq 0 \;\; \forall_i$

$$L_p \equiv \frac{1}{2} \|w\|^2 - \sum_{i=1}^{L} \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^{L} \alpha_i \tag{3.18}$$

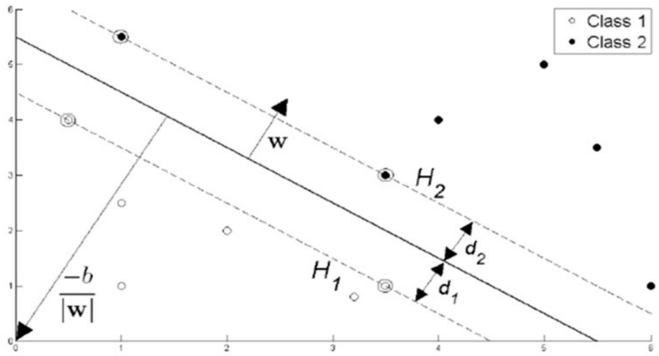


Figure 3.15 Hyperplane through two linearly separable classes [235].

By differentiating Equation 3.18 with respect to *w* and setting, and the derivatives to zero we find *w*.

$$\frac{\partial L_P}{\partial W} = 0 \Rightarrow w = \sum_{i=1}^{L} \alpha_i y_i x_i \tag{3.19}$$

By differentiating Equation 3.18 with respect to b and setting the derivatives to zero we find the *b* (minimises), and the α (maximises)

$$\frac{\partial L_P}{\partial b} = 0 \Rightarrow \sum_{i=1}^{L} \alpha_i y_i = 0 \tag{3.20}$$

Substituting the last two equations Equation (3.19) and Equation (3.20) into Equation (3.18) gives a new equation which is dependent on α. Therefore, it requires maximizing.

$$L_D \equiv \sum_{i=1}^{L} \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \, \alpha_j y_i y_j x_i . x_j \;\; such\ that\ \alpha_i \;\geq 0 \; \forall_i \tag{3.21}$$

Then

$$L_D \equiv \sum_{i=1}^{L} \alpha_i - \frac{1}{2} \alpha^T H \alpha \;\;\; S.t \;\;\; \alpha_i \geq 0 \;\; \forall_i \tag{3.22}$$

$where \quad \sum_{i=1}^{L} \alpha_i y_i = 0$

$H_{ij} = y_i y_j x_i \,.\, x_j$

$x_i . x_j = x_i^T \,.\, x_j$

L_D is a dual form of primary L_P that requires dot product for each input.

Maximising L_D and to do that we need to find:

$$max_{\propto} \left[\sum_{i=1}^{L} \alpha_i - \frac{1}{2}\alpha^T H \alpha\right] \quad S.t\ \alpha_i \geq 0 \ \forall_i \ and \sum_{i=1}^{L} \alpha_i y_i = 0 \qquad (3.23)$$

Then we perform the Quadratic Programming solver that returns α, then we substitute Equation 3.19 to find *w*, and *b* from Equation 3.20.

Any set of coordinates satisfying Equation 3.20 which is a support vector x_s will have the following form: $y_s(w.x_s + b) = 1$, where "." as the inner product.

substituting in Equation (3.19)

$$y_s(\sum_{m\in S} \alpha_m\, y_m x_m . x_s + b) = 1 \qquad (3.24)$$

Where *S* is defined as a set of indices of the support vector, that can be determined by finding the indices *i where* $\alpha_i > 0$. Multiplying by y_s and then using $y_s^2 = 1$ form Equations (3.12) and (3.13)

$$y_s^2(\sum_{m\in S} \alpha_m\, y_m x_m . x_s + b) = y_s \qquad (3.25)$$

The equation can be written as:

$$b = y_s^{-1} - \sum_{m\in S} \alpha_m y_m x_m . x_s \qquad (3.26)$$

It is preferable to get a mean over all of the support vectors in *S* rather than random support vectors x_s as follows:

$$b = \frac{1}{N_s}\sum_{s\in S}(y_s - \sum_{m\in S} \alpha_m y_m x_m \cdot x_s) \qquad (3.27)$$

After this, we get the variables *w* and *b* that define separating the optimal orientation of the hyperplane and hence the SVM.

The ELM is a learning algorithm for a one hidden layer feed-forward neural network. It randomly selects the input weights and analytically sets the output weights of this neural network. In theory, the ELM is an extremely fast learner. In some cases, this algorithm can present the best generalisation efficiency and it can learn much more quickly than other learning algorithms for the feed-forward neural networks [236-238].

The functions that describe the single hidden layer feed-forward network can be written as follows [237]:

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_i \,.\, x_j + b_i) = o_j, \quad (3.28)$$

Where $j = 1 \ldots N$.

N = arbitrary distinct sample $(x_i\,,\, t_i)$

$x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in \mathbb{R}^n$

$t_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T \in \mathbb{R}^m$

$g_i(x)$ is an activation function; $g_i(x) = g(w_i . x_j + b_i)$.

$\tilde{N}$ is the number hidden nodes.

Oj is the output.

Standard single hidden layer feedforward networks (SLFNs), where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ connect the ith hidden node and the input nodes. $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the weight vector connecting the ith hidden node and the output nodes, and b_i is the threshold of the ith hidden node. $w_i \cdot x_j$ denotes the inner product of w_i and x_j. The output nodes are linear in this chapter.

N samples with zero error mean that

$\sum_{j=1}^{\tilde{N}} \|o_j - t_j\| = 0$ i.e., there exist β_i, w_i and b_i such that

$$\sum_{i}^{\tilde{N}} \beta_i g(\, w_i \,.\, x_j + b_i) = t_j, \;\; j = 1, \;\; \cdots, N \quad (3.29)$$

The above N equations can be written compactly as

$H\beta = T$ where

$H(w_1, \ldots, w_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}}, x_1, \ldots, x_N) =$

$$\begin{bmatrix} g(w_1.x_1 + b_1) & \ldots & g(w_{\tilde{N}}.x_1 + b_{\tilde{N}}) \\ \vdots & \ldots & \vdots \\ g(w_1.x_N + b_1) & \cdots & g(w_{\tilde{N}}.x_N + b_{\tilde{N}}) \end{bmatrix}_{N\,x\,\tilde{N}} \tag{3.30}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N}\,x\,m} \tag{3.31}$$

And

$$T = \begin{bmatrix} \mathrm{t}_1^T \\ \vdots \\ \mathrm{t}_N^T \end{bmatrix}_{N\,\mathrm{x}\,m} \tag{3.32}$$

H is called the hidden layer. The ith column of H is the ith hidden node output concerning inputs $x_1, x_2, \ldots, x_N$.

ELM is a rapid learning process and exhibits better generalisation performance [237, 239, 240]. But the most important properties of the application make ELM suitable for our case when encountering a lack of data, because the ELM is an effective classification tool for the small training database as well [241]. Figure 3.16 illustrates the ELM structure.

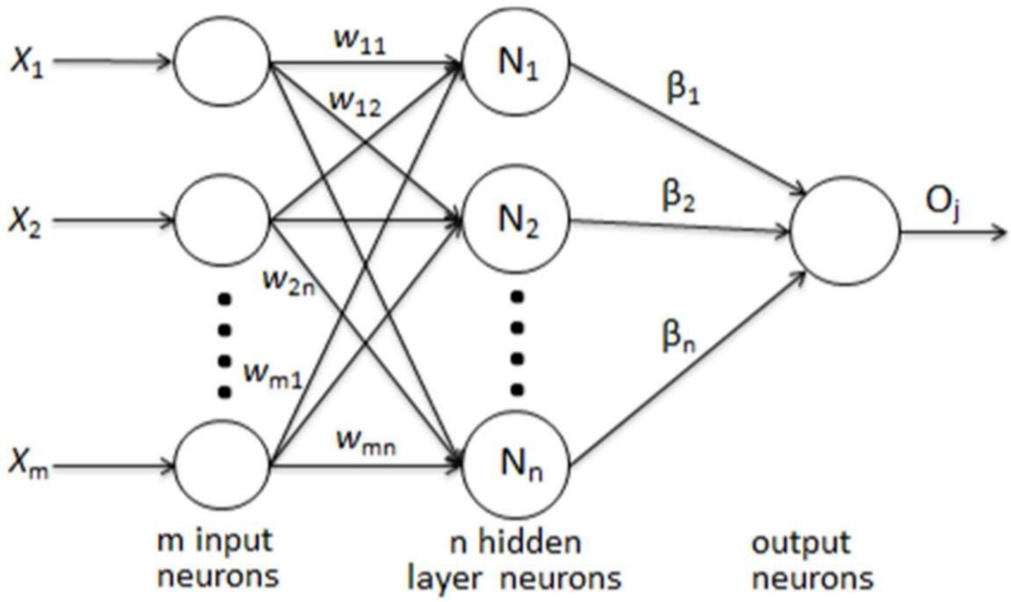


Figure 3.16 ELM structure [242].

3.3.14 Classification algorithm performance

A cross-validation strategy was used to evaluate the performance of the classification technique used by the new AR system. The term "cross-validation" generally refers to the breaking down of a dataset into both a training and a testing set. The training set contains mapped data that is employed to train the classifier, whereas the testing set contains unmapped data that is employed to test the correctness of the classifier. Usually, multiple samples of the dataset are executed in multiple rounds of cross-validation.

Furthermore, the K-fold cross-validation method was used in this study and for this purpose and the dataset was split into (K) subgroups. The testing group was one subgroup of the original dataset, and the training group was made up of the remaining subgroups of the original dataset (K-1). Therefore, each time one of the K subsets is used as the test group, the other K-1 subgroups are collected together to form a training group to check all (K) samples in the original dataset. Then it is important that the number of rounds achieves the same number (K) of samples in the subgroups. The K-fold cross-validation method is commonly used in many studies because it provides an unbiased estimate of the probability of error [1, 243].

In this study will use a value of K=5; because 80% of the dataset for training and 20% of dataset for testing is usually used [244]. Therefore, in this step, the dataset was divided into five groups. Each group contains six participants. In the first round, the first group was used as a testing dataset, and the remaining 24 samples (4 groups) were used as the training dataset. In the second round, the second group represented a testing dataset, and the remaining 24 samples (4 groups) were used as the training dataset. We repeated this until five rounds (K = 5), and finally, we computed the mean accuracy for these five rounds.

In fact, the sensitivity, specificity, and accuracy were computed to quantify the performance of the classification algorithm. Sensitivity measures the rate of correctly classified samples in the positive (ASD) class, specificity measures the rate of correctly classified samples in the negative (TD) class, and accuracy measures the rate of correctly classified samples in both positive (ASD) and negative (TD) classes where [245]:

Sensitivity = number of ASD classified correctly / number of all children classified as ASD.

Specificity = number of TD classified correctly / number of all children classified as TD.

Accuracy = number of users classified correctly / number of all classified children.

Here in Tables 3.4 and 3.5 are an example shows the calculation of the accuracy, sensitivity, and specificity:

Table 3.4 consider the binary classification, form of the classification in the data classification task.

	Condition		
Outcome of the diagnostic test	Positive	Negative	Total
Positive	TP	FP	TP + FP
Negative	FN	TN	FN + TN
Total	TP + FN	FP + TN	N = TP + FN + FP + TN

TP: Number of ASD Truly classified.

FP: Number of ASD Falsely classified.

TN: Number of TD Truly classified.

FN: Number of TD Falsely classified.

TP + FN: Number of classified subjects as positive.

TP + FN + FP + TN: The total number of classified subjects.

Sensitivity = TP / (TP + FN).

Specificity = TN / (TN + FP).

Accuracy = (TN + TP) / (TN + TP + FN + FP).

Table 3.5: Example in action to calculate accuracy, sensitivity and specificity.

	Condition		
	Positive	Negative	Total
Positive	3	0	3
Negative	1	2	3
Total	4	2	6

Sensitivity = 3 / 4 = 75%.

Specificity = 2 / 2 = 100%.

Accuracy = 5 / 6 = 83.33%.

In addition, the classification between ASD and TD part in this system was tested by a different dataset (National Database for Autism Research (NDAR) in the USA, and Scientific Institute IRCCS Eugenio Medea in Italy). The test results of the classification part have been published in the two papers [2, 4].

3.3.15 Classifier evaluation

The main evaluation method that was employed to check the performance of the classifier was accuracy, i.e., the rate of correctly classified data in the test group. In each round, the accuracy was computed by using five-fold cross-validation. In addition, in each fold, one block was selected as the test block, and the remaining four blocks were used as a training set. Then the accuracy of each round was calculated and the average accuracy of five rounds. In addition, a statistical analysis is applied in order to illustrate the experimental. As mentioned previously, the experiments are based on the collected data by the system. Moreover, the extraction and classification parts in this system were tested by a different dataset (National Database for Autism Research (NDAR) in the USA, and the Scientific Institute IRCCS Eugenio Medea in Italy). The test results of the extraction and classification parts have been published in several papers [2-6].

3.3.15.1 The NDAR dataset

The NDAR dataset contains three tasks: The data were collected after seventeen High-Risk children (HR) for autism and fifteen Low-Risk children (LR) for autism performed the specific task, between the ages of one and three years. These tasks are as follows:

- **Shape sorter task**: In this task, the child was asked to insert an object into a box with interchangeable lids (see Figure 3.17). Each lid has a slot identical to but only slightly larger than the cross-section of the shape to be inserted. Each shape was presented six times: three times in an initial vertical direction and three in an initial horizontal direction. Please refer to the technical paper [246], for more detail.

Figure 3.17 Equipment for the first task [246].

In this task, the results were as follows: The SVM was able to classify participants successfully. The classification accuracy reached a maximum accuracy of 83.3% (sensitivity = 80% and specificity = 100%). Overall mean accuracy, specificity, and sensitivity rates were also calculated: mean sensitivity = 76.5%, mean specificity = 66.7% and mean accuracy = 71.9%. However, the ELM was also able to classify participants successfully. The classification accuracy reached a maximum accuracy of 100% (sensitivity = 100% and specificity = 100%) overall mean accuracy, specificity, and sensitivity rates were also calculated. The overall mean classification for sensitivity, specificity, and accuracy was 78.5%, 66.7%, and 72.5%, respectively.

- **Inserting the ball**: In this task, the child was asked to fling a small ball into a clear plastic tub for three trials (see Figure 3.18. A). Then the child was asked to insert a ball into a clear tube open at both ends (see Figure 3.18. B). Please refer to the technical paper [247], for more detail.

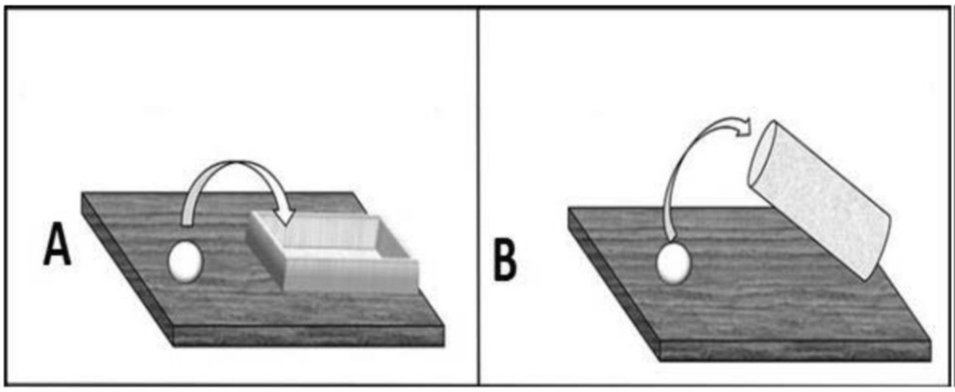


Figure 3.18 Equipment for the second task [247].

In inserting the ball task, The SVM method was able to categorise children in this study successfully. In the first part, the maximum classification accuracy was 100% (sensitivity 100% and specificity 100%) and the overall mean classification was calculated: mean sensitivity = 75.00%, mean specificity = 73.33% and mean accuracy = 74.19%. In the second part, the maximum accuracy was 83.33 % (sensitivity 89.41% and specificity 76.00%). The overall mean classification for sensitivity, specificity, and accuracy was 76.47%, 73.33%, and 75.0%, respectively. However, the ELM was able to classify children successfully. In the first part, the maximum classification accuracy was 100%

(sensitivity 100% and specificity 100%) and the overall mean accuracy, specificity, and sensitivity rates were also calculated: mean sensitivity = 74.12%, mean specificity = 73.33% and mean accuracy = 73.67%. In the second part, the maximum accuracy was 100.0% (sensitivity 100.0 % and specificity 100.0%). The overall mean classification for sensitivity, specificity, and accuracy was 82.35%, 80.0%, and 81.67%, respectively.

- **Cubes task**: In this task, the child was asked to place a block into a large open box, for three trials (shown in Figure 3.19 A). Then the child was asked to place four similar blocks on a target block to make a tower (shown in Figure 3.19 B). Depending on the level of the child's skill, towers can range in height from two to five blocks. Please refer to the technical paper [219], for more detail.

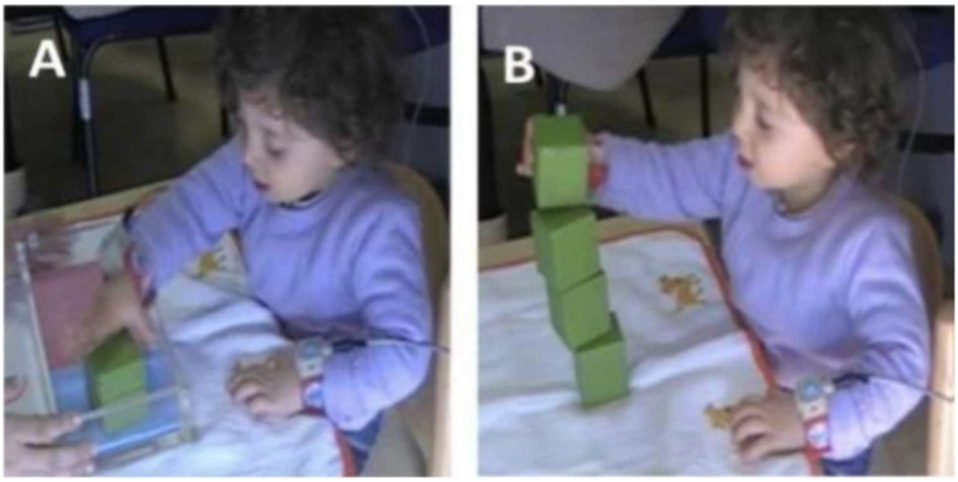


Figure 3.19 Equipment for the third task [219].

In the cubes task, the SVM method was able to categorise children in this study successfully. In the first part, the mean classification accuracy was 67.74% and in the second part 70.0%. However, The ELM method was also able to categorise children in this study successfully. In the first part, the mean classification accuracy was 74.29% and in the second part, 60.0%. Table 3.6 summarises the results of using SVM and ELM classifiers in the NDAR datasets.

Table 3.6: The results of using SVM and ELM classifiers in NDAR datasets.

Task	SVM classifier	ELM classifier
Shape Sorter task.	71.9%	72.5%
Insert the small ball into tub.	74.19%	73.67%
Insert the ball into tube.	75.00%	81.67%
Place a block into a large open box.	67.74%	74.29%
Build a tower of cubes.	70%	60.00%

3.3.15.2 The IRCCS Eugenio Medea dataset

The IRCCS Eugenio Medea dataset contains one task: The data were collected after fifteen autistic children and fifteen non-autistic children, aged between two and four years, performed a specific task.

- The reach and drop task: The assessment was initiated when the child's hands were placed at a determined site and the ball was placed at a distance away from them of around twenty centimetres. The study task consisted of the child picking up the tiny rubber ball and dropping it into an open box (shown in Figure 3.20). For each child participant, there were ten trials of this task [1].
- The reach and drop task results: The SVM classified kids successfully achieved the overall mean classification as exemplified by the following findings: average sensitivity was 91.0% while average specificity was 98.1%, and intermediate accuracy was 93.8%.

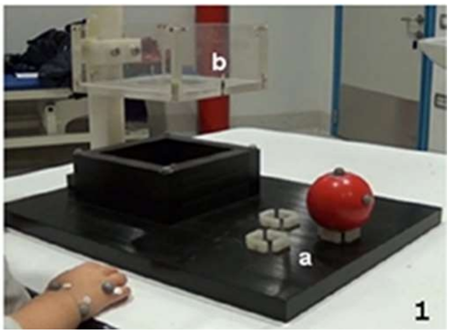


Figure 3.20 Equipment for the IRCCS task [1].

3.4 Results of the new system

This study compared fifteen school autistic children aged (48-60 months) with fifteen non-autistic children (50-59 months). The data concerning the characteristics of the participants is detailed in Table 3.7.

Table 3.7: Participant characteristics.

	Autistic children	Non-autistic children
Number	15	15
Male: Female	12:3	10:5
Age (months)	48-60	50-59

As mentioned before, we used SVM and ELM in the system as a classifier. The study performed SVM that divided the database randomly into two groups; dataset group for training and dataset group for testing. The SVM and ELM algorithms were repeated five times (K = 5). Each time, the SVM selected 6 different children as the test dataset and 24 different children as the training dataset. In addition, we traced the execution and documented the results in each round.

The SVM was able to successfully classify participants. The classification performance reached maximum accuracy = 100%, maximum sensitivity = 100%, and specificity = 100%. Overall mean accuracy, specificity, and sensitivity rates were also calculated. The results were as follows: 83.3%, 76.7%, and 89.3%, respectively.

The ELM classifier was able to successfully classify children. The classification performance reached maximum accuracy = 100%, maximum sensitivity = 100%, and specificity = 100%. Overall mean accuracy, specificity, and sensitivity rates were also calculated. The results were as follows: 90.0%, 86.7%, and 93.34%, respectively.

However, the LDA algorithm was able to enhance the classification of participants in the SVM classifier and there was a negative effect on the ELM classifier. The classification accuracy reached maximum accuracy = 100%, maximum sensitivity = 100%, and specificity = 100%. Overall mean accuracy, specificity, and sensitivity rates were also calculated. The results were as follows: 86.7% for all performance values; sensitivity, specificity, and accuracy. In Table 3.8 and Figure 3.21 we show the mean difference in sensitivity, specificity, and accuracy between the classifiers.

Table 3.8: Difference in mean Sensitivity, Specificity, and Accuracy of classifiers.

Classifier	Sensitivity	Specificity	Accuracy
SVM	89.3%	76.7%	83.3%
ELM	93.34%	86.7%	90.0%
SVM and LDA	86.7%	86.7%	86.7%

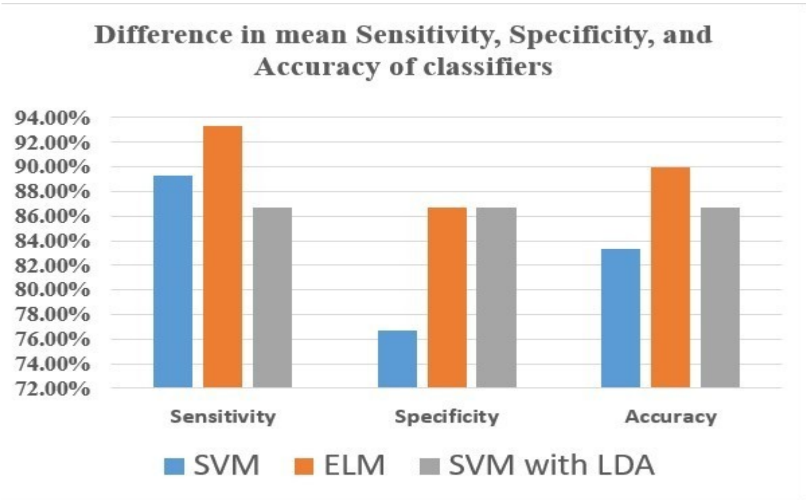


Figure 3.21 Difference in mean Sensitivity, Specificity, and Accuracy of classifiers.

The column graph in Figure 3.21 shows the comparison between the performance of linear SVM without LDA, ELM and SVM with LDA in the dataset. The experiment of our method performed on the dataset replicated the trend of the findings for the [2, 4] datasets. Indeed, it is clear that the ELM method outperformed the linear SVM method without LDA and the linear SVM method with LDA. Also, the LDA enhanced specificity and accuracy, but it had a negative affect on sensitivity.

As we noted from the experiments, the time interval between the start of playing movement and the contact with the object is greater in ASD comparing to TD. Also, ASD movements were faster and larger, with more distance use of space. In addition, autistic children showed more errors during the tasks and repeated the attempts compared to the TD children.

3.5 Conclusion

This study sought to explore the essential characteristics of AR systems that help in diagnosing and treating autistic children. In addition, it clarified the design criteria and the challenges associated with this type of AR system by conducting a review of the related works. Based on this review, we proposed an AR system as a case study that included design decisions and considered the appearance aspects of the design. Based on our evaluations, we believe that our proposed design can accommodate most of the criteria (Table 3.3 required for designing an effective AR system for autism.

Further research on the proposed design is needed to evaluate our new AR system on a range of children within the targeted group. We need to assess the AR system manipulation tasks in terms of their effectiveness in diagnosing autism and improving the lives of autistic children. The goals of the AR tasks are embodied in understanding human emotions, communication, and talking. Such work could also be extended in the future to other neurodevelopmental cases (e.g., intellectual disability, developmental delays without intellectual disability, or developmental coordination disorders in order to determine whether the developed classifier is specific to ASD, or whether it can be used for neurodevelopmental disorders in general.

Ethical considerations

This thesis was produced as part of the "Implementation of an Augmented Reality Game to Track Upper Limb Movement in Autistic Children," study number ETH18-2710 approved by the University of Technology Sydney (Sydney, New South Wales, Australia. The children's participation in this study was discussed with their legal guardian, and informed consent was obtained. The guardians were informed that they could withdraw consent at any time and for any reason. Also, we demonstrated videos (with de-identified participants) for our school in candidate assessment three (CA3).

Chapter Four
A Novel Virtual Sample Generation Algorithm

(The content of this chapter has been published in *Algorithms Journal* [8])

Deep neural networks are successful learning tools for building nonlinear models. However, a robust deep learning-based classification model needs a large dataset. Indeed, these models are often unstable when they use small datasets. To solve this issue, which is particularly critical in light of the possible clinical applications of these predictive models, researchers have developed approaches such as virtual sample generation. Virtual sample generation significantly improves learning and classification performance when working with small samples. The main objective of this study is to evaluate the ability of the proposed virtual sample generation to overcome the small sample size problem, which is a feature of the automated detection of a neurodevelopmental disorder, namely autism spectrum disorder. Results show that our method enhances diagnostic accuracy from 84%-95% using virtual samples generated on the basis of five actual clinical samples. The present findings show the feasibility of using the proposed technique to improve classification performance even in cases of clinical samples of limited size. Accounting for concerns in relation to small sample sizes, our technique represents a meaningful step forward in terms of pattern recognition methodology, particularly when it is applied to diagnostic classifications of neurodevelopmental disorders. Moreover, the proposed technique has been tested with other available benchmark datasets. The experimental outcomes showed that the accuracy of the classification that used virtual samples was superior to the one that used original training data without virtual samples.

4.1 Introduction

Deep learning computational models consist of many processing layers in order to learn representations of data with many levels of abstraction [248], as shown in Figure 4.1. Deep learning is a machine learning mechanism that employs many layers of nonlinear information processing for the purposes of supervised or unsupervised learning, feature extraction, and classification. Deep learning algorithms depend heavily on the number of data and computing power [249-251]. Accordingly, they do not perform to an optimal level with small datasets. Recent advances in terms of adequate amounts of collected data and increased levels of computing power [249] have led to a resurgence in neural network research, and this has in turn sparked a new era of (deep) machine learning research.

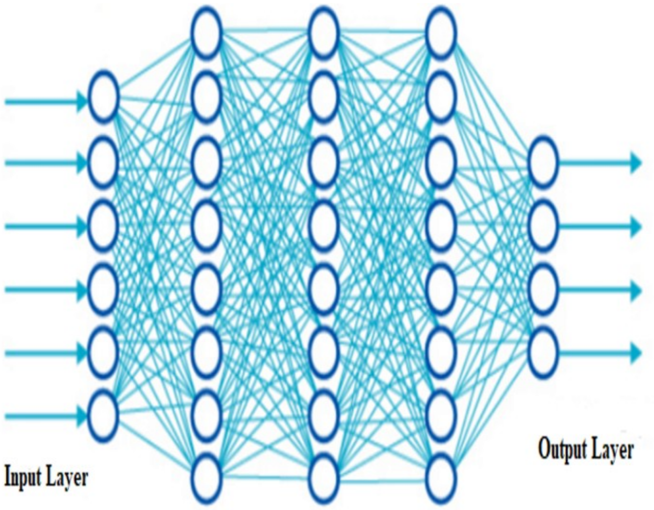


Figure 4.1 Example of a deep neural network.

Limited dataset sizes are considered to be one of the most critical concerns in terms of early prediction [252]. Unfortunately, this issue is particularly common in the case of diseases such as rare hereditary diseases (e.g., Maple syrup urine disease [253]), unique study populations (e.g., Kashin Beck Disease (KBD) [254]), individually-tailored treatments (e.g., tumour treatment [255]), isolated environments (e.g., Ebola [256]), emergency situations (e.g., autoimmune systemic diseases and vasculitides [257, 258]), and neurological or psychiatric disorders [2, 259].

The size of available clinical samples is ordinarily small in the field of medical research due to the intrinsic prevalence of disorders and other factors such as elevated costs for patient recruitment and the limited time available for evaluations. Small sample sizes significantly limit the ability of pattern recognition methods to predict or classify individuals of different groups correctly, and this leads to inaccurate classification performance. Indeed, supervised classification methods require a training dataset in order to learn the classification algorithm that best differentiates the two groups and a testing dataset in order to verify the classification performance on previously unseen data. In medical research, samples and datasets are usually not large enough to perform the training phase and the testing phase of the computerised algorithm on a totally independent dataset. This renders this methodology prone to over fitting. Nevertheless, different methods have been proposed to overcome this critical issue. The main three methods are Mega Trend Diffusion (MTD), Functional Virtual Population (FVP), and Multivariate Normal synthetic sample generation (MVN).

- **Mega Trend Diffusion (MTD):**

MTD was proposed in [260] based on the information diffusion method that uses fuzzy theories to fill missing data [261, 262]. The main difference between MTD and the information diffusion method is that MTD employs a general diffusion function to scatter a collection of data across the whole dataset, while the information diffusion method diffuses each sample separately [262]. MTD merges mega diffusion with data trend estimation to control the symmetrical expansion issue and to increase the learning accuracy in flexible manufacturing system scheduling. Both the diffusion-neural-network and megatrend-diffusion require membership function values such as extra information, and that means the appearance possibility for each input attribute and the number of input attributes needed for artificial neural network training. This process makes the calculation more complicated and lengthier in duration. In addition, the membership function values basically do not hold any managerial meaning [260, 263]. Lastly, the MTD technique is applied to simulated systems. Therefore, it is not clear what this technique achieves in real system situations [264].

- **Functional Virtual Population (FVP):**

The functional virtual population was developed in [265]. FVP is based on data domain expansion methods (i.e., left, right, and both sides) for small datasets [262]. The FVP method operates by adding virtual samples for training assistance and acquiring scheduling knowledge in dynamic industrialising systems. The strategy includes data decreasing, data increasing, and mixed data to form a functional virtual population. The generated virtual samples increase the learning performance of neural networks [266]. The FVP technique was the first method that was proposed for small dataset managing, and it was developed to extend the domain of attributes and produce virtual samples for the purposes of constructing early scheduling knowledge. It is based on a trial and error procedure and requires many steps to complete the process [267]. This method has significant limitations when applied to systems including nominal variables or high variance between stages [268].

- **Multivariate Normal synthetic sample generation (MVN):**

MVN has two parameters, and each parameter contains more than one piece of information. One parameter sets the centre of the distribution, and the other parameter determines the dispersion and the width of the spread from side to side of the distribution centre [269]. The MTD and FVP methods extend the dataset by enlarging the domains of the feature dataset while the MVN method synthetically produces input specifying single dimensional multivariate normal data sample generation [264, 270]. MVN synthetic sample generation uses multivariate covariance dependencies among basic samples. In addition, it maintains the ingrained noise of samples [264] . MVN utilises the covariance matrix that summarises the interaction between different components of data [271].

4.2 Virtual sample generation technique

As mentioned above, the main goal of MTD, FVP, and MVN is generating virtual samples. Virtual Sample Generation (VSG) is a data preprocessing technique proposed to increase the prediction accuracy for the small-dataset issue [272]. This idea was first proposed in 1998 by [273] to improve the recognition (object and speech recognition) performance for image and sound datasets.

Another work [267] used the bootstrap method to generate virtual samples in order to enhance the accuracy of a computerised algorithm derived from a small clinical sample in predicting radiotherapy outcomes. Results showed that when the amount of training data and learning accuracy were directly correlated to the prediction, the outcome of radiotherapy steadily increased from 55%-85%.

The study published in [274] developed a novel technique, based on random variate generation, that was used in the early phase of data gathering to handle a DNA microarray categorisation issue. This technique was employed to search for discrete collections in the DNA microarray and to consider outliers as various sets in a nonlinear method. This technique generated virtual samples from the original small datasets based on binary classification. Moreover, the UCI database [275] experiments were used in this study. Finally, the results showed that this method largely enhanced the accuracy of machine learning in the early stages of DNA microarray data, and it significantly helped in terms of solving the problem of the extremely small training dataset with nonlinear data or outliers.

The work in [276] proposed a method based on a generative adversarial network put together with a deep neural network. The generative adversarial network was trained with the training group to generate virtual sample data which in turn increased the training group. Then, the deep neural network classifier was trained with the virtual samples. After that, they tested the classifier with the original test group, and the indicators validated the effectiveness of the method for multi-classification with a small sample size. As an experimental case, the method was then used to recognise the stages of cancers with a small classified sample size. The empirical results verified that the proposed method achieved better accuracy than traditional methods.

The study [277] aimed to generate a synthetic sample that reflected the attributes of the people listed in the "Health Survey for England". They used data from the “Health Survey for England” to define gender and the age-dependent distributions of continuous variable risk factors such as weight, height, number of cigarettes/day, and units of alcohol/week and the prevalence of binary risk factors such as diabetes and smoking status. Spearman rank correlations including gender and age were defined for these risk variables. A table of normally-distributed random numbers was produced. The sample was then generated utilising a reverse lookup of the gamma distribution value using the random percentiles for continuous variables or setting a binary variable to one when the random percentile fell below the prevalence threshold. The new method produced big virtual samples with risk factor distributions very closely matching those of the real “Health Survey for England” population. This sample can be utilised to model the likely impact of new therapies or predict mortality.

The work published in another paper [252] developed a new method of VSG called genetic algorithm-based virtual sample generation, which was based on the integrated effects and restrictions of data attributes. The first procedure determined the appropriate range by utilising MTD functions. Then, a genetic algorithm was applied to accelerate the generation of the most appropriate virtual samples. The last step was verification of the performance of the proposed method by comparing the results with two different forecasting models. The experimental outcomes showed that the performance of the method that used virtual samples was superior to the one that used original training data without virtual samples.

Consequently, the proposed technique can enhance learning performance significantly when working with small samples. Many of these previous sample generation approaches have shown a good ability to enhance prediction and classification performance. However, none of them are based on the overlapping that exists in the features stage. Accordingly, this study presents a new virtual sample technique that also considers avoiding overlaps among each of the features in the different classes. Furthermore, this study is distinguished by its ability to generate and deal with a huge amount of virtual samples that is hundreds of thousands of samples instead of tens or hundreds of virtual samples.

4.3 The proposed method

This section presents detailed steps to illustrate the method we developed in the present work, from data selection to the construction and generation of the virtual samples necessary to build the models and the classification tool. A schematic description of the whole procedure is shown in Figure 4.2. The procedure involved three steps: the first step was the selection of a small set of samples from a whole dataset; the second was the application of the VSG method to generate new samples; and the third step included data prediction and classification.

The algorithm automatically ranked the top discriminative features and excluded the non-discriminative features. In the second step, a small set of samples was randomly selected, called selected samples, from the entire dataset, and the remaining samples were used as testing data. In the third step, we applied the proposed VSG method to generate new virtual samples, depending on the selected samples from the second step. Then, virtual samples were added to the selected samples for the next learning step. In the fourth step, the combined dataset (i.e., the original dataset plus the newly-generated virtual samples) was used to train the deep neural network, then we checked the classifier performance by classifying the testing data.

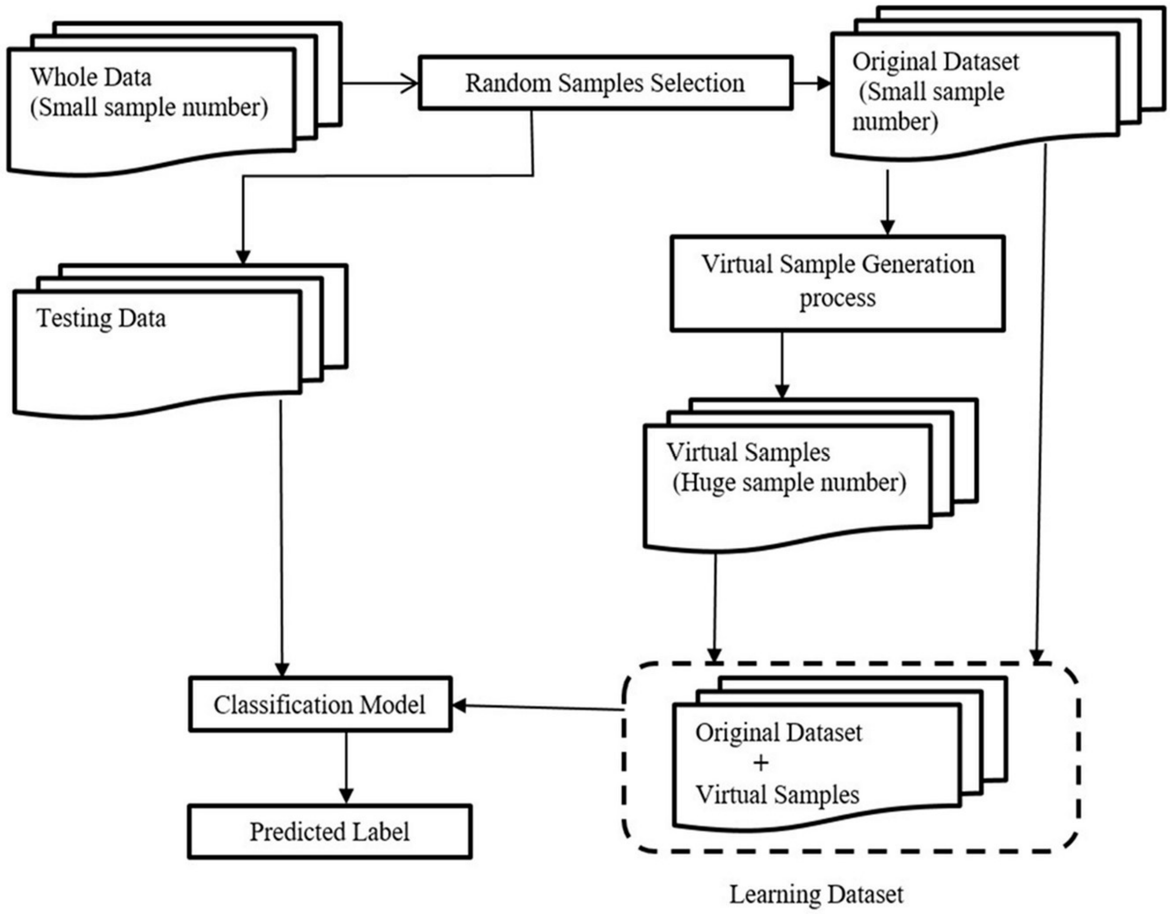


Figure 4.2 Flowchart of the whole procedure with three different steps:
(1) selection of a small sub-sample from the entire dataset and the remaining samples used as testing data; (2) application of the VSG method depending on the selected samples from the first step; (3) data prediction and classification.

The first step of the proposed technique was to select samples randomly. These numbers were selected randomly from intervals of 3-10 as a small database for the first time; then, these numbers were set for all experiments to achieve comparisons. The number of randomly selected samples were 3, 5, 6, and 9. From each class, the Selected Samples

(SS) were from the whole dataset (30 samples), and the remaining 24, 20, 18, and 12 samples, respectively, were the testing data.

The features of small selected samples of two different classes are represented in two matrices A and B with the same size as follows:

Let $I = \{1, \dots, m\}$ denote the indices of the rows of matrices A and B.

Let $J = \{1, \dots, n\}$ denote the indices of the column of matrices A and B.

Let a_{ij} denote the value of the element A[i, j].

Let b_{ij} denote the value of the element B[i, j].

The algorithm started by finding the following:

The minimum value for each feature in matrix A is NA. It appears as a single dimension matrix as follows:

$$NA_J = \min_{\forall i} a_{ij}$$

Where $j \in [1, n]$

The maximum value for each feature in matrix A is MA. It appears as a single dimension matrix as follows:

$$MA_J = \max_{\forall i} a_{ij}$$

Where $j \in [1, n]$

The mean value for each feature in matrix A is MeA. It appears as a single dimension matrix as follows:

$$MeA_J = \frac{1}{n}\sum_{i=1}^{n} a_{ij} \; , j = 1, \dots, n$$

The minimum value for each feature in matrix B is NB. It appears as a single dimension matrix as follows:

$$NB_J = \min b_{ij\ i \in I}\ , j = 1, \dots, n$$

The maximum value for each feature in matrix B is MB. It appears as a single dimension matrix as follows:

$$MB_J = \max b_{ij\ i \in I}\ , j = 1, \dots, n$$

The mean value for each feature in matrix B is MeB. It appears as a single dimension matrix as follows:

$$MeB_J = \frac{1}{n}\sum_{i=1}^{n} b_{ij}\ , j = 1, \dots, n$$

Then, for each iteration, starting from the first elements in the matrices NA, MA, NB, and MB to the last elements in these matrices, these four elements were the inputs of Equation (4.1) to check if there was any overlapping occurring in between them. If there was no overlap, then we expanded the intervals by Equations (4.5) and (4.6), otherwise, we tried to solve the overlaps by Equation (4.2).

$For\ j = 1, \dots, n$

$$f(NA_j, MA_j, NB_j, MB_j) =$$

$$\begin{cases} Equations\ (4.5)\ and\ (4.6), & if\ \left(NA_j \geq MB_j\right) \vee \left(NB_j \geq MA_j\right) \\ P\left(NA_j, MA_j, NB_j, MB_j\right), & otherwise \end{cases} \tag{4.1}$$

The second process was the random variant generation to create new Virtual Samples (VS) based on the maximum, minimum, and mean calculated for every discriminative feature in each group in the selected samples (SS). After this, the virtual samples were added to SS by Equations (4.3) and (4.4). The number of generated samples could vary in terms of N (N = 10,000, 25,000, 50,000, 100,000, 200,000, and 300,000). All generated feature j values were between the interval (Min_j, Max_j) where Min_j is the minimum value in feature j and Max_j is the minimum value in feature j, while with a normal Gaussian distribution, the VS was generated by Equation (4.7).

The third step was the training phase of the system: SS and VS were employed as learning data and the residual data in the first step as testing data. Lastly, the classification performance was evaluated by using the Softmax classifier.

The proposed work can be summarised as follows: the new virtual samples were generated, depending on the original small dataset; the original dataset plus the newly-generated virtual samples both can be added to the training samples to expand the training dataset for machine learning significantly. Thus, our method can produce virtual samples closely related to the original datasets by applying a normal Gaussian distribution. The proposed work aims to make the classification model more stable and overcome the common limitations of the classification performance.

The working condition of the proposed system was that there were no overlaps between intervals. The system checked if the intervals had a direct ideal case, and the system started to generate a virtual sample without any pre-processing. Otherwise, the system tried to get rid of overlaps if success expanded the interval range, and it would start to generate virtual samples between the known intervals. Otherwise, it would skip to the next features.

4.4 Virtual sample generation method

In the third step, for each discriminative feature, we applied the VSG method described in Algorithm 1 to generate virtual samples and then added them to the original dataset to produce a combined dataset for learning. The proposed method consisted of two parts.

The first was the pre-processing technique, which searched for the rational interval (without overlaps) of each feature with the corresponding feature in another class. The second part was the random variant generation that increased the training dataset based on the original dataset for each rational feature. The code structure of the VSG method was as follows.

Algorithm 1 The algorithm for virtual sample generation.

```
Input: Small number of samples as class A and B.
Output: Hundreds of thousands or millions of samples (N).
1: loop J = 1: Number_ of_ Features // Number of Columns in the Matrix
2: {Find the Max, Min and Mean for each feature in class A and B}
3: {Initialize MaxA = The Maximum value in the feature J in matrix A}
4: {Initialize MinA = The Minimum value in the feature J in matrix A}
5: {Initialize MeanA = The Mean value for all values in the feature J in matrix A}
6: {Initialize MaxB = The Maximum value in the feature J in matrix B}
7: {Initialize MinB = The Minimum value in the feature J in matrix B}
8: {Initialize MeanB = The Mean value for all values in the feature J in matrix B}
9: If (MinA >= MaxB) or (MinB >= MaxA) // Ideal cases see Figure 4.3
10: {If (MaxA > MaxB) // Expand the intervals before Generating N virtual samples
11: MaxA = MaxA + MeanA
12: else
13: MaxB = MaxB + MeanB
14: if (MinA < MinB) // Expand the intervals
15: MinA = MinA - MeanA
16: else
17: MinB = MinB - MeanB}
// Generate N virtual sample with a normal distribution as follows
// Rand generates random numbers an N (rows) × columns random matrix, where a
//Gaussian distribution of these numbers was achieved by the following equations.
18: VGA = MinA + (MaxA - MinA) * sum (rand (N, columns), 2) / columns;
19: VGB = MinB + (MaxB - MinB) * sum (rand (N, columns), 2) / columns;
20: else // Not ideal case. Shown in Figure 4.5
```

21: call Algorithm 2 // The preprocessing
22: end loop
23: {New-samples = Small number of samples + N samples}

4.4.1 The pre-processing method

The purpose of the pre-processing step was to preface the discriminative feature within the selected samples precisely. This step was mandatory in order to avoid overlapping of the sequence of corresponding discriminative features before generating new virtual samples. As an example, one of the datasets tested in this work included two groups: one Related Group (RG) including participants with autism spectrum disorders and an Unrelated Group (URG), which means healthy participants. It was clear that it was not reasonable to overlap the two different groups during the generation; therefore, this event was precluded by the pre-processing method as the following mathematical statements:

For each feature, its values are ordered in descending sort for class *A* in matrix *MlsA*, as follows:

$$MlsA_I = \max a_{ij_{i\in I-1}}, \{j = 1, \dots, n\}, MlsA_i \geq MlsA_{i+1}$$

For each feature, its values are ordered in ascending sort for class *A* in matrix *mlsA*, as follows:

$$mlsA_I = \min a_{ij_{i\in I-1}}, \{j = 1, \dots, n\}, mlsA_i \geq mlsA_{i+1}$$

For each feature, its values are ordered in descending sort for class *B* in matrix *MlsB*, as follows:

$$MlsB_I = \max b_{ij_{i\in I-1}}, \{j = 1, \dots, n\}, MlsB_i \geq MlsB_{i+1}$$

For each feature, its values are ordered in ascending sort for class *B* in matrix *mlsB*, as follows:

$$mlsB_I = \min b_{ij_{i\in I-1}}, \{j = 1, \dots, n\}, mlsB_i \geq mlsB_{i+1}$$

Here, Equation (4.2) tries to handle overlaps, and after each execution of this equation, it checks the ideal case.

$$p(NA_j, MA_j, NB_j, MB_j, c) = \begin{cases} Equations\ (4.5)\ and\ (4.6);if\ (NA_j \geq MB_j) \vee (NB_j \geq MA_j) \\ stop\ and\ delete\ current\ column,\ \ if\ (c = I) \\ p(mlsA_c,MA_j,NB_j,MB_j,c+1);\ if\ (NA_j<NB_j)\wedge(MB_j<MA_j)\wedge(MeA_j-NA_j)>(MA_j\geq MeA_j) \\ p(NA_j,MlsA_c,NB_j,MB_j,c+1);\ if\ (NA_j<NB_j)\wedge(MB_j<MA_j)\wedge(MeA_j-NA_j)>(MA_j-MeA_j) \\ p(mlsA_c,MA_j,NB_j,MB_j,c+1);\ if\ (NA_j>NB_j)\wedge(MB_j<NA_j)\wedge(MB_j<MA_j)\wedge(MeA_j-NA_j)\leq(MB_j\geq MeB_j) \\ p(NA_j,MlsA_c,NB_j,MB_j,c+1);\ if\ (NA_j>NB_j)\wedge(MB_j>NA_j)\wedge(MB_j<MA_j)\wedge(MeA_j-NA_j)>(MB_j-MeB_j) \\ p(NA_j,MA_j,mlsB_c,MB_j,c+1);\ if\ (NB_j>NA_j)\wedge(MA_j<NB_j)\wedge(MA_j<NB_j)\wedge(MeB_j-NB_j)\leq(MA_j\geq MeA_j) \\ p(NA_j,MA_j,NB_j,MlsB_c,c+1);\ if\ (NB_j>NA_j)\wedge(MA_j>NB_j)\wedge(MA_j<MB_j)\wedge(MeB_j-NB_j)>(MA_j-Me\ \ _j) \\ p(NA_j,MA_j,NB_j,MlsB_c,c+1);\ if\ (NB_j<NA_j)\wedge(MA_j<NB_j)\wedge(MeB_j-NB_j)\leq(MB_j-MeB_j) \\ p(NA_J,MA_j,NB_j,MmlsA_c,c+1);\ if\ (NB_j<N\ \ _j)\wedge(MA_j<M\ \ _j)\wedge(MeB_j-NB_j)>(MB_j\geq MeB_j) \end{cases} \quad (4.2)$$

If it succeeded in handling overlap (c < I), then Equations (4.5) and (4.6) were executed to expand the intervals, which were followed by Equation (4.7), which would be executed to generate N virtual features. Otherwise, the feature would be deleted and would not be taken into the consideration for the purposes of generating virtual samples. Furthermore, the columns (features) in matrices A and B that failed to generate virtual numbers according to the previous Equation (4.2) would be deleted, and two new matrices with the new column dimension (H) would be generated NA_{IH} and NB_{IH}

H denotes the new number of the column of matrices NA and NB after deletion of the unsuccessful columns (features) from matrices A and B, where $H \leq J$.

In addition, the generated single dimension matrices GAh_{N1}, $h = 1,\ldots, H$ and GBh_{N1}, $h = 1,\ldots, H$ were combined horizontally into a single matrix NGA_{NH} and NGB_{NH} respectively, as shown in Equation (4.3).

N = number of virtual samples.

$$\begin{aligned} NGA_{NH} &= [GA1_{N1} \cdots GAh_{N1}], \qquad h = H \\ NGB_{NH} &= [GB1_{N1} \cdots GBh_{N1}], \qquad h = H \end{aligned} \tag{4.3}$$

Finally, in Equation (4.4) combined vertically the NA_{IH} with NGA_{NH} matrices, and NB_{IH} with NGB_{NH} into a single matrices $AA_{(I+N)H}$ and $BB_{(I+N)H}$ respectively. These matrices (data) will be used as learning data for the classifier.

$$\begin{aligned} AA_{(I+N)H} &= \begin{bmatrix} NA_{IH} \\ NGA_{NH} \end{bmatrix} \\ BB_{(I+N)H} &= \begin{bmatrix} NB_{IH} \\ NGB_{NH} \end{bmatrix} \end{aligned} \tag{4.4}$$

The pre-processing technique primarily grouped samples based on their spatial relationship. The pre-processing algorithm can be summarised as follows:

Step 1: Find the maximum value, minimum value, and computed arithmetic mean for each feature for each class. Following this, check for any possible overlaps between the maximum values and minimum values for each feature in the first class with the corresponding feature in the second class. It is necessary to exclude possible overlaps (ideal cases, as can be seen in Figure 4.3) before generating meaningful virtual samples.

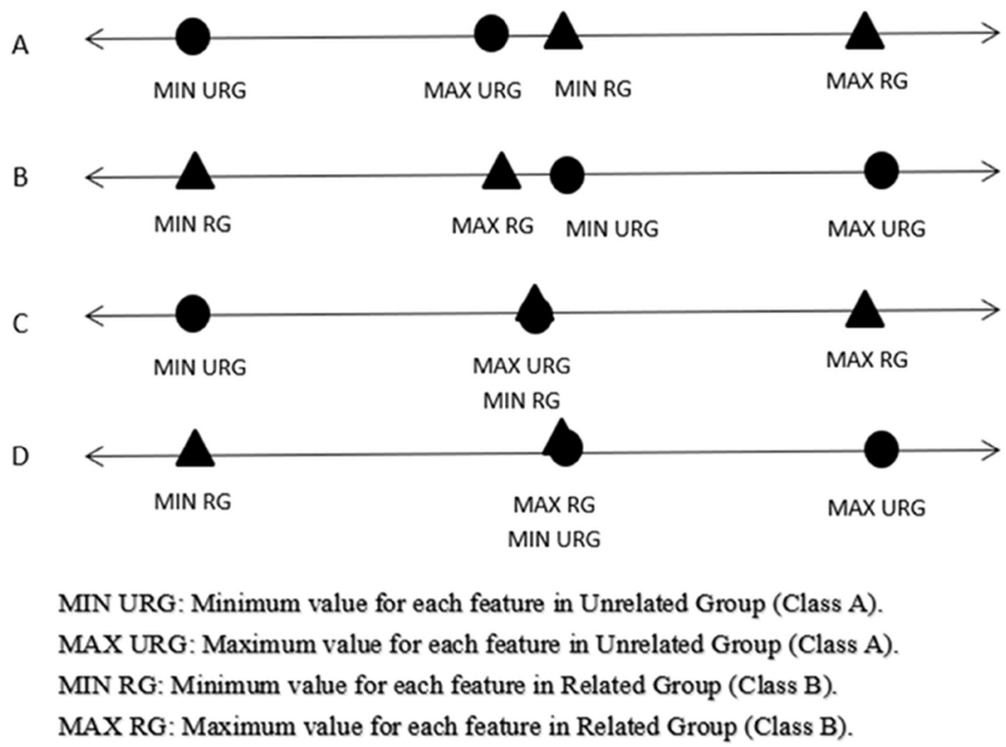


Figure 4.3 Ideal cases where there is no overlapping between the feature and the same feature in the corresponding class.

Step 2: After having verified the absence of overlaps, expand the sides using the mean for each feature and generate meaningful virtual samples based on a Gaussian distribution, as shown in Figure 4.4.

Now, expand the intervals, both right and left sides, by Equations (4.5) and (4.6) respectively.

$$EMAX(MA_j, MB_j) = \begin{cases} MA_j = MA_j + MeA_j \ , \ MA_j > MB_j \\ MB_j = MB_j + MeB_j \ , \ otherwise \end{cases} \tag{4.5}$$

$$EMIN(MA_j, MB_j) = \begin{cases} NA_j = NA_j - MeA_j \ , \ NA_j < NB_j \\ NB_j = NB_j - MeB_j \ , \ otherwise \end{cases} \tag{4.6}$$

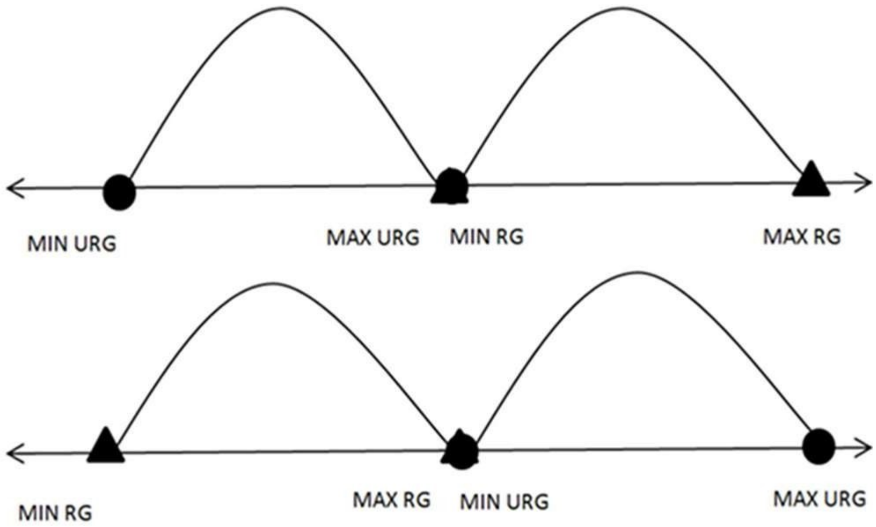
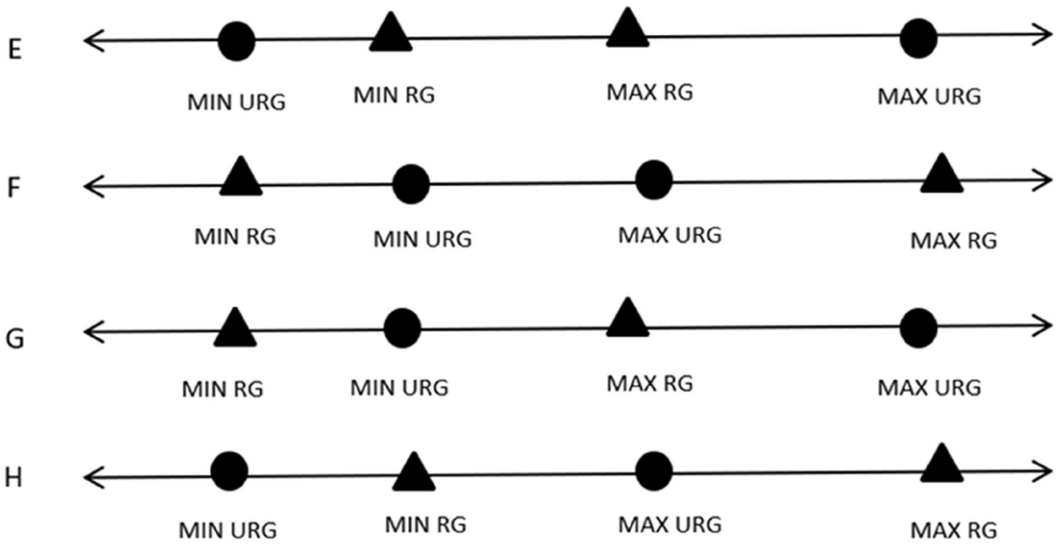


Figure 4.4 Generating meaningful virtual samples based on a Gaussian distribution

Step 3: In the case of overlaps, as in the case depicted in Figure 4.5 of the process, start removing overlaps by moving the points that are far from the mean.



MIN URG: Minimum value for each feature in Unrelated Group (Class A).
MAX URG: Maximum value for each feature in Unrelated Group (Class A).
MIN RG: Minimum value for each feature in Related Group (Class B).
MAX RG: Maximum value for each feature in Related Group (Class B).

Figure 4.5 Overlapping cases between the feature and the same feature in the corresponding class.

Step 4: Repeat Steps 1-3 until all overlaps based on "Algorithm 2" have been removed. After this, the process generates virtual samples based on a Gaussian distribution, Equation (4.7).

During this step, after the collections were formed using the pre-processing method for each discriminative feature, the mean and standard deviation for each group for all discriminative features were recalculated before moving on to the next process. The distribution example of the virtual sample distribution after the pre-processing method is illustrated in Figure 4.6.

Algorithm 2 is the algorithm for solving overlapping.

```
{Input: Feature with overlapping} // A and B are two different classes //
Output: Feature without overlapping
{Find the MaxA, MaxB, MinA, MinB, MeanA, and MeanB
{Initialize MlsA = the features in descending order for class A}
{Initialize mlsA = the features in ascending order for class A}
{Initialize MlsB = the features in descending order for class B}
{Initialize mlsB = the features in ascending order for class B}
{Initialize C = 1} // counter
Loop Until ((MinA >= MaxB) or (MinB >= MaxA)) // Ideal case Figure 4.3.
{C = C+1
if (MinA < MinB and MaxB < MaxA) // Case E: Figure 4.5.
if (MeanA - MinA <= MaxA - MeanA)
MinA = mlsA[C]
else
MaxA = MlsA[C]
if (MinA > MinB and MaxB > MinA and MaxB < MaxA)// Case G: Figure 4.5
if (MeanA - MinA <= MaxB - MeanB)
MinA = mlsA[C]
else
MaxA = MlsA[C]
if (MinB > MinA and MaxA > MinB and MaxA < MaxB) // Case H: Figure 4.5
```

```
if (MeanB - MinB <= MaxA - MeanA)
MinB = mlsB[C]
else
MaxB = MlsB[C]
if (MinB < MinA and MaxA < MaxB) // Case F: Figure 4.5.
if (MeanB - MinB <= MaxB - MeanB)
MinB = mlsB[C]
else
MaxB = MlsB[C]
end loop
{Back to Algorithm 1}
```

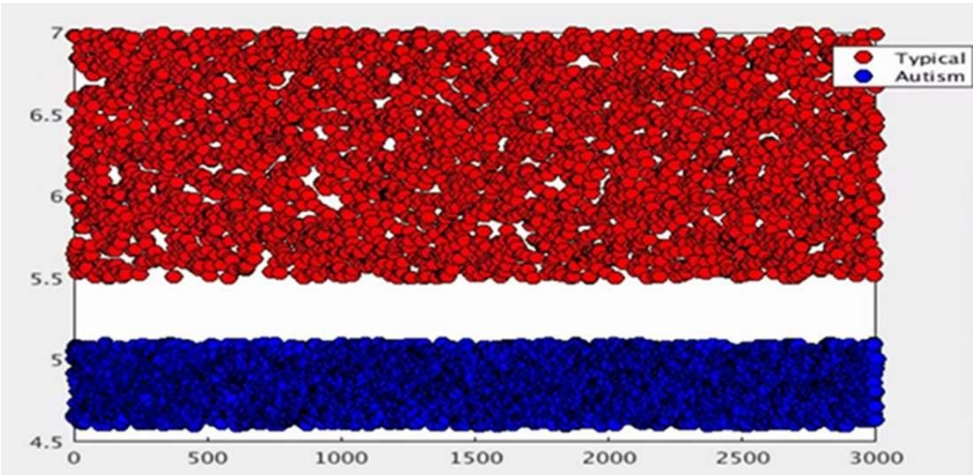


Figure 4.6 Data distribution after pre-processing method.

4.4.2 Random virtual generation technique

In the second process, Equation (4.7) generated new virtual samples depending on the maximum, minimum, mean, and standard deviation computed for every collection of all discriminative features and added them to the corresponding group of the original dataset Equations (4.3) and (4.4). A MATLAB function [278] was used to generate a virtual sample in a normal distribution. The normal distribution in general of the virtual sample is illustrated in Figure 4.7.

The Gaussian distribution is very widely used for distributions in probability, statistics, and many natural phenomena [279]. For example, heights, weight, blood pressure, the temperature during a year, and IQ scores follow a normal distribution. The Gaussian normal distribution is helpful because of the central limit theorem, which is a very important theorem in statistics. In addition, this avoids accumulation of all values in a few points only.

$$G(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \quad where\ G(X) \in [MIN, MAX] \qquad (4.7)$$

where:

X is a normal random variable.

μ is a mean.

σ is a standard deviation.

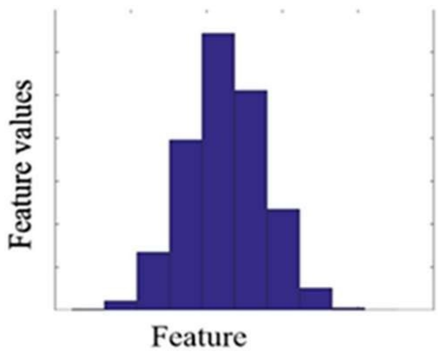


Figure 4.7 Normal distribution for one feature after generating the virtual sample.

4.5 Experiment

4.5.1 Datasets

The above-described method was developed using a dataset provided by Scientific Institute IRCCS Eugenio Medea. In addition, the proposed technique was tested with other available benchmark datasets. These benchmark datasets are relevant to ASD by the fact that all of them are in the medical field.

4.5.1.1 IRCCS Meda dataset

The first dataset was collected at Scientific Institute IRCCS Eugenio Medea in Italy (Bosisio Parini, Italy). The dataset included data from 30 participants divided into two groups: 15 children with a clinical diagnosis of Autism Spectrum Disorder (ASD) and 15 participants with typical development (TD). For each participant, 17 kinematic parameters (numerical features) related to an upper-limb movement were registered [1]. In the original work, a feature selection algorithm was used to identify the seven features that best differentiated participants with ASD from healthy controls. In the present work, our algorithm randomly selected six participants (from now on, samples) as an original small dataset, with three samples for each group (ASD and healthy children), and the remaining 24 samples were used as the testing dataset. For comparison, we generated 10,000 virtual samples using the proposed method for every collection in the first trial, and then, this rose by the following numbers each time: 25,000, 50,000, 100,000, 200,000, and 300,000. The identical learning procedure was repeated for five rounds.

4.5.1.2 E-Coli dataset

The second dataset was the Escherichia coli dataset [275, 280] and this included values of the measurements of E. coli bacteria (commonly found in the human gut). This dataset included 336 samples. Each sample belonged to one of eight classes, where each class referred to a type of E. coli bacteria. Each sample consisted of eight attributes; see the dataset description listed in Table 4.1. The training and testing set for this dataset were chosen as follows. We selected 77 samples for each of the first two classes (CP and IM) to ensure that we had binary classes with an equal sample number. Then, three samples were selected randomly from each of the selected class. These three samples represented the original small dataset. Starting from these three samples, the proposed method generated 10,000 virtual samples for every class for the first time. Then, the number of virtual samples were increased as follows: 25,000, 50,000, 100,000, 200,000, and 300,000 from each class. To give an example of this, the total number of training samples for the first round was 20,006 (six actual samples plus 20,000 virtual samples). The remaining 148 samples were used as testing data. After that, we repeated the experiment, randomly selecting five samples as an original small dataset, from each class of the E. coli dataset. Doing so, the total number of training samples was 10 plus the virtual samples. The remaining 144 samples were used as testing samples, and these steps were repeated five times.

4.5.1.3 Breast tissue dataset

The third dataset was the Breast Tissue dataset [280, 281], and this included values of the measurements relative to the electrical impedance of freshly-excised tissue from the breast. This dataset included 106 samples where each sample belonged to one of six classes. Six classes of freshly-excised tissue were studied using electrical impedance measurements: carcinoma, fibroadenoma, mastopathy, glandular, connective, and adipose. The training and the testing set for this dataset were chosen as follows. We selected 15 samples for each of the first two classes (carcinoma and fibroadenoma) to ensure that we had binary classes with an equal samples number. Then, three samples were selected randomly from each of the selected classes. These three samples represented the original small dataset. Starting from these three samples, the proposed method generated 10,000 virtual samples for every class for the first time. Then, the number of virtual samples were increased as follows: 25,000, 50,000, 100,000, 200,000, and 300,000 from each class. To give an example of this, the total number of training samples for the first round was 20,006 (six actual samples plus 20,000 virtual samples). The remaining 24 samples were used as testing data. After that, we repeated the experiment, randomly selecting five samples as an original small dataset, from each class of the breast tissue dataset. By doing so, the total number of training samples was 20 plus the virtual samples. The remaining 20 samples were used as testing samples. These steps were repeated five times.

Table 4.1 Description of the three datasets.

Datasets	Number of Samples	Number of Attributes	Number of Classes
IRCCSMeda	30	17	2
E. coli	336	8	8
Breast Tissue	106	9	6

4.5.2 Classification techniques

In this study, a deep neural network was implemented with a stacked auto-encoder, using the MATLAB Neural Network Toolbox™ auto-encoder functionality [282] for training a deep neural network and to classify an ASD. In more detail, a stacked auto-encoder is a neural network composed of various layers of sparse auto-encoders where the outputs of each layer are connected to the inputs of the sequential layers. stacked auto-encoder are suitable for numerical dataset (such as our data), the other alternative is Convolutional Auto-encoders (CAE), but CAE helps in extracting visual features. Thus, stacked autoencoder is justified selection. The structure of an auto-encoder is illustrated in Figure 4.8.

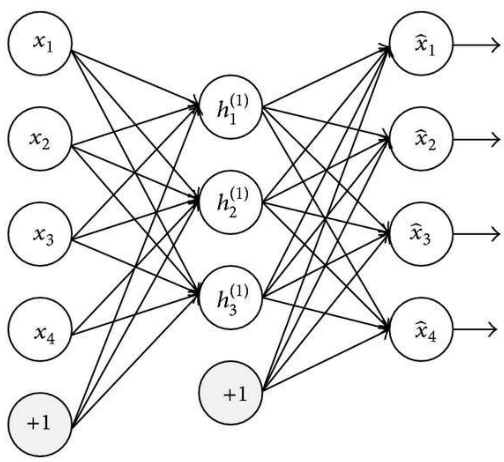


Figure 4.8 Structure of auto-encoder [283].

For classification, we used Softmax, which is a layer located in the top layer of the fully-connected layer network (shown in Figure 4.9). Its non-linearity predicts the probability distribution over classes that have been given the input sentence [282, 284]. Details of the Softmax method were described in [285]. In the present work, we applied Softmax to validate and evaluate the performance of our newly-proposed method.

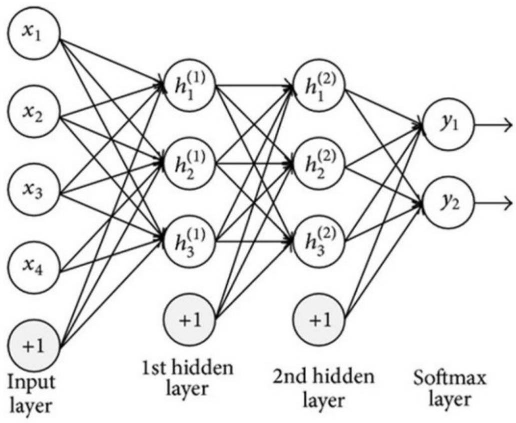


Figure 4.9 Stacked auto-encoder with Softmax classifier [283].

In a neural network, it is not feasible to determine the goodness of the network topology only on the basis of the number of inputs and outputs [285]. Usually, a neural network must be empirically specified, selecting a model and determining the hidden layer quantity with the minimum validation error rate among multiple variants of the models [285]. Our first experiment was implemented by using a deep learning network with 100 hidden nodes in each layer. In the second experiment, we reduced the number of hidden nodes to 50, whereas in the third experiment, the first layer included 100 hidden nodes and the second layer 50 hidden nodes. This procedure was carried out for investigating the effect of the hidden node size in the deep learning network. We continued until we obtained satisfactory results. The best performance was 100 hidden nodes in the first layer and 50 hidden nodes in the second layer.

4.5.3 Experimental results

This section presents the results of the experiments on the three datasets (IRCCS Medea, E. coli, and Breast Tissue) in detail, for each dataset.

For the IRCCS Medea dataset, the averages accuracies are shown in Figure 4.10-4.12 and listed in Table 4.2.

For the E. coli dataset, the average accuracies are shown in Figure 4.10 and 4.14 and are listed in Table 4.3.

The third dataset was the Breast Tissue dataset. The average accuracies after performing these steps are shown in Figure 4.15 and 4.16 are listed in Table 4.4.

Table 4.2: The results of the average accuracy using the IRCCS Medea dataset.

Number of original samples for each class	Number of the virtual samples for each class	Total number of virtual samples	Number of samples for training	Number of the sample for testing	Deep learning without VSG	Linear SVM Accuracy without VSG	Accuracy with VSG and deep learning	Improvement
3	10,000	20,000	20,006	24	66.7%	70.83%	79.2%	8.37%
3	25,000	50,000	50,006	24	66.7%	70.83%	79.2%	8.37%
3	50,000	100,000	100,006	24	66.7%	70.83%	75.0%	4.17%
3	100,000	200,000	200,006	24	66.7%	70.83%	75.0%	4.17%
3	200,000	400,000	400,006	24	66.7%	70.83%	75.0%	4.17%
3	300,000	600,000	600,006	24	66.7%	70.83%	75.0%	4.17%
5	10,000	20,000	20,010	20	65.0%	75.0%	90.0%	15.0%
5	25,000	50,000	50,010	20	65.0%	75.0%	95.0%	20.0%
5	50,000	100,000	100,010	20	65.0%	75.0%	85.0%	10.0%
5	100,000	200,000	200,010	20	65.0%	75.0%	90.0%	15.0%
5	200,000	400,000	400,010	20	65.0%	75.0%	90.0%	15.0%
5	300,000	600,000	600,010	20	65.0%	75.0%	85.0%	10.0%
6	10,000	20,000	20,012	18	72.2%	77.78%	94.4%	16.62%
6	25,000	50,000	50,012	18	72.2%	77.78%	88.9%	11.12%
6	50,000	100,000	100,012	18	72.2%	77.78%	88.9%	11.12%
6	100,000	200,000	200,012	18	72.2%	77.78%	83.3%	5.52%
6	200,000	400,000	400,012	18	72.2%	77.78%	88.9%	11.12%
6	300,000	600,000	600,012	18	72.2%	77.78%	83.3%	5.52%
9	10,000	20,000	20,018	12	75.0%	83.33%	83.3%	0%

9	25,000	50,000	50,018	12	75.0%	83.33%	83.3%	0%
9	50,000	100,000	100,018	12	75.0%	83.33%	91.8%	8.33%
9	100,000	200,000	200,018	12	75.0%	83.33%	91.8%	8.33%
9	200,000	400,000	400,018	12	75.0%	83.33%	83.3%	0%
9	300,000	600,000	600,018	12	75.0%	83.33%	83.3%	0%

Table 4.3: The results of the average accuracy using the E. coli dataset.

Number of original samples for each class	**Number of the virtual samples for each class**	**Total number of virtual samples**	**Number of samples for training**	**Number of the sample for testing**	**Deep learning without VSG**	**Linear SVM Accuracy without VSG**	**Accuracy with VSG and deep learning**	**Improvement**
3	10,000	20,000	20,006	148	50.0%	83.8%	92.8%	9.0%
3	25,000	50,000	50,006	148	50.0%	83.8%	93.9%	10.1%
3	50,000	100,000	100,006	148	50.0%	83.8%	93.9%	10.1%
3	100,000	200,000	200,006	148	50.0%	83.8%	91.9%	8.1%
3	200,000	400,000	400,006	148	50.0%	83.8%	93.2%	10.1%
3	300,000	600,000	600,006	148	50.0%	83.8%	91.2%	8.1%
5	10,000	20,000	20,010	144	50.0%	85.4%	93.8%	8.4%
5	25,000	50,000	50,010	144	50.0%	85.4%	91.0%	5.6%
5	50,000	100,000	100,010	144	50.0%	85.4%	94.4%	9.0%
5	100,000	200,000	200,010	144	50.0%	85.4%	91.0%	5.6%
5	200,000	400,000	400,010	144	50.0%	85.4%	94.4%	9.0%
5	300,000	600,000	600,010	144	50.0%	85.4%	90.3%	4.9%

6	10,000	20,000	20,012	142	50.0%	85.2%	92.3%	7.1%
6	25,000	50,000	50,012	142	50.0%	85.2%	93.0%	7.8%
6	50,000	100,000	100,012	142	50.0%	85.2%	92.3%	7.1%
6	100,000	200,000	200,012	142	50.0%	85.2%	91.5%	6.3%
6	200,000	400,000	400,012	142	50.0%	85.2%	92.9%	7.7%
6	300,000	600,000	600,012	142	50.0%	85.2%	91.5%	6.3%
9	10,000	20,000	20,018	136	50.0%	91.9%	93.4%	1.5%
9	25,000	50,000	50,018	136	50.0%	91.9%	92.6%	0.07%
9	50,000	100,000	100,018	136	50.0%	91.9%	94.9%	3.0%
9	100,000	200,000	200,018	136	50.0%	91.9%	94.9%	3.0%
9	200,000	400,000	400,018	136	50.0%	91.9%	95.6%	3.74%
9	300,000	600,000	600,018	136	50.0%	91.9%	94.9%	3.0%

Table 4.4 : The results of the average accuracy using the Breast Tissue dataset.

Number of original samples for each class	**Number of the virtual samples for each class**	**Total number of virtual samples**	**Number of samples for training**	**Number of the sample for testing**	**Deep learning without VSG**	**Linear SVM Accuracy without VSG**	**Accuracy with VSG and deep learning**	**Improvement**
3	10,000	20,000	20,006	24	79.17%	87.5%	95.8%	8.3%
3	25,000	50,000	50,006	24	79.17%	87.5%	95.8%	8.3%
3	50,000	100,000	100,006	24	79.17%	87.5%	95.8%	8.3%
3	100,000	200,000	200,006	24	79.17%	87.5%	95.8%	8.3%

3	200,000	400,000	400,006	24	79.17%	87.5%	91.7%	4.2%
3	300,000	600,000	600,006	24	79.17%	87.5%	91.7%	4.2%
5	10,000	20,000	20,010	20	85.0%	85.0%	90.0%	5.0%
5	25,000	50,000	50,010	20	85.0%	85.0%	95.0%	10.0%
5	50,000	100,000	100,010	20	85.0%	85.0%	90.0%	5.0%
5	100,000	200,000	200,010	20	85.0%	85.0%	90.0%	5.0%
5	200,000	400,000	400,010	20	85.0%	85.0%	90.0%	5.0%
5	300,000	600,000	600,010	20	85.0%	85.0%	90.0%	5.0%
6	10,000	20,000	20,012	18	88.89%	88.89%	88.89%	0%
6	25,000	50,000	50,012	18	88.89%	88.89%	88.89%	0%
6	50,000	100,000	100,012	18	88.89%	88.89%	88.89%	0%
6	100,000	200,000	200,012	18	88.89%	88.89%	88.89%	0%
6	200,000	400,000	400,012	18	88.89%	88.89%	94.4%	5.51%
6	300,000	600,000	600,012	18	88.89%	88.89%	94.4%	5.51%
9	10,000	20,000	20,018	12	91.70%	91.70%	91.7%	0%
9	25,000	50,000	50,018	12	91.70%	91.70%	100%	8.3%
9	50,000	100,000	100,018	12	91.70%	91.70%	100%	8.3%
9	100,000	200,000	200,018	12	91.70%	91.70%	95.8%	4.19%
9	200,000	400,000	400,018	12	91.70%	91.70%	91.7%	0%
9	300,000	600,000	600,018	12	91.70%	91.70%	91.7%	0%

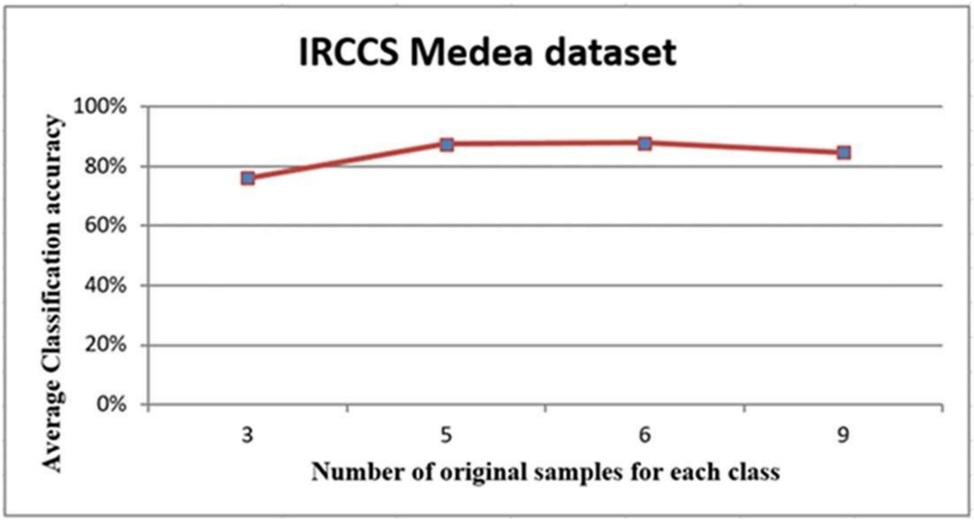


Figure 4.10 The curve of the average accuracies of the simulated datasets.

The graph in Figure 4.10 depicts the relationship between the number of original samples for each class that was used to generate the virtual sample and the average of classification accuracy. The graph showed a growth in the relationship between six samples, followed by a levelling out. Overall, from this graph, it is possible to conclude that the number of original samples was not critical for generating the virtual sample. Moreover, this demonstrated that the proposed method was efficient with only a small number of original samples.

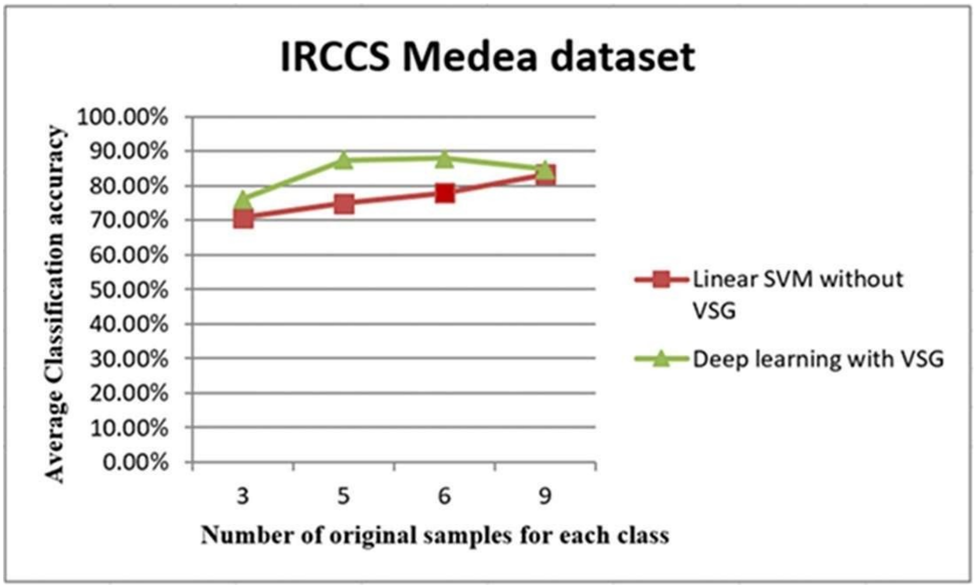


Figure 4.11. The trend of average accuracy using the IRCCS dataset.

The line graph in Figure 4.11 shows the comparison between the performance of linear SVM without Virtual Sample Generation (VSG) and deep learning with the VSG number in the IRCCS Medea dataset. The x-axis of this graph shows the original samples for each class that were used to generate the virtual sample in deep learning and the training sample for linear SVM, while the average of classification accuracy is the y-axis.

The plot depicted in Figure 4.12 shows distinctly that the present deep learning method with the proposed method exceeded in the first three intervals the linear Support Vector Machine method (SVM) used in [1]. In the 3, 5, and 6 samples, the proposed method showed better results in terms of classification performance when using a limited sample size compared to traditional linear SVM.

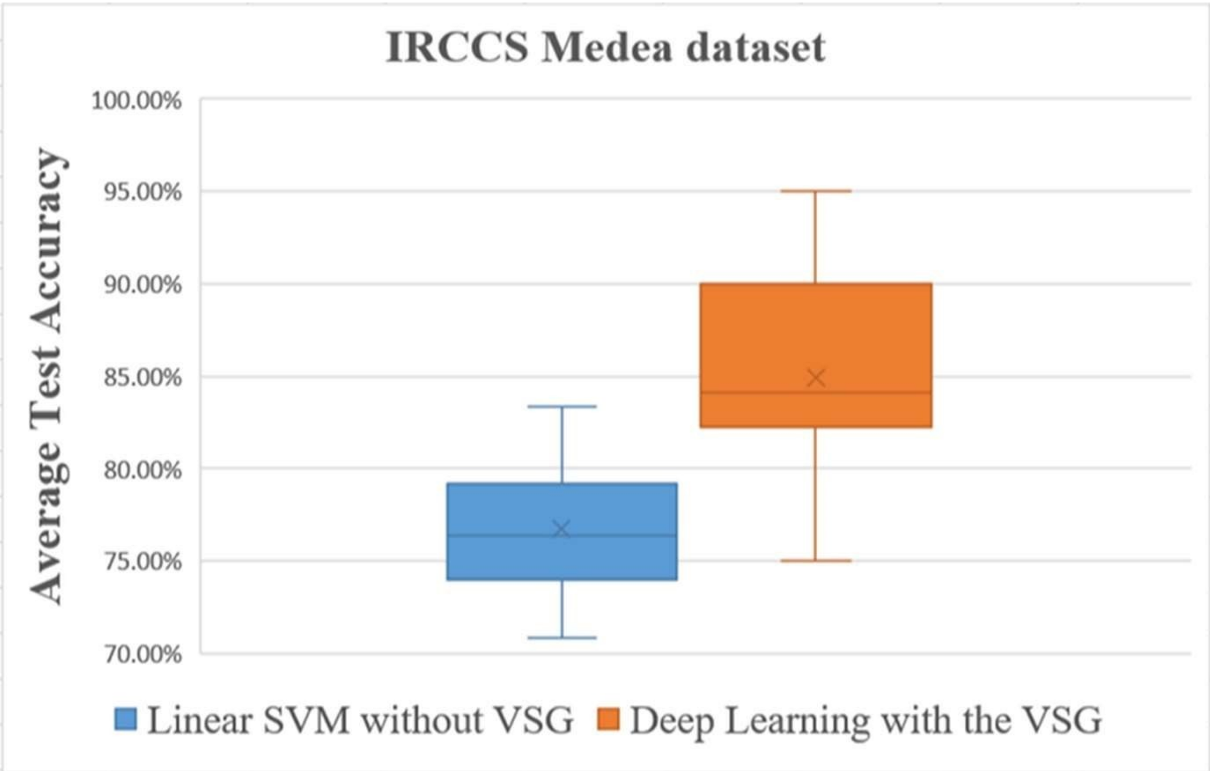


Figure 4.12 Overall comparisons of the experimental results using the IRCCS Medea dataset.

The box plot in Figure 4.12 clearly shows that the present deep learning method with the proposed method exceeded in overall comparisons the linear SVM method using the IRCCS Medea dataset.

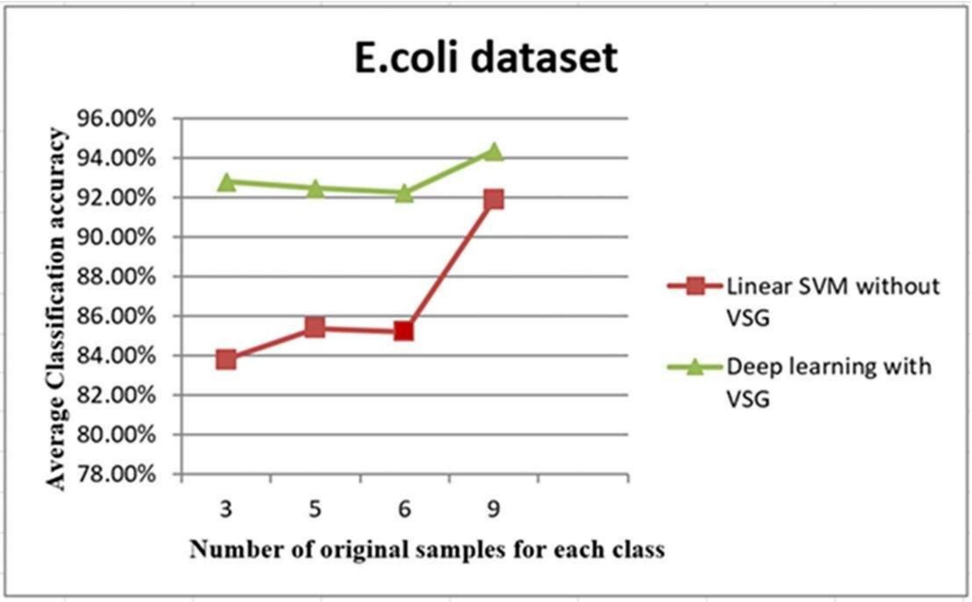


Figure 4.13 The trend of average accuracy using the E. coli dataset.

The line graph in Figure 4.13 shows the comparison between the performance of linear SVM without VSG and deep learning with VSG number in the E. coli dataset. The x-axis of this graph shows the original samples for each class that were used to generate the virtual sample in deep learning and the training sample for linear SVM, while the average of classification accuracy is the y-axis. In addition, the experiment of our method performed on the E. coli dataset replicated the trend of findings for the IRCCS Medea dataset. Indeed, it was clear that deep learning with the proposed method outperformed the linear SVM method without VSG for the first of all the intervals considered.

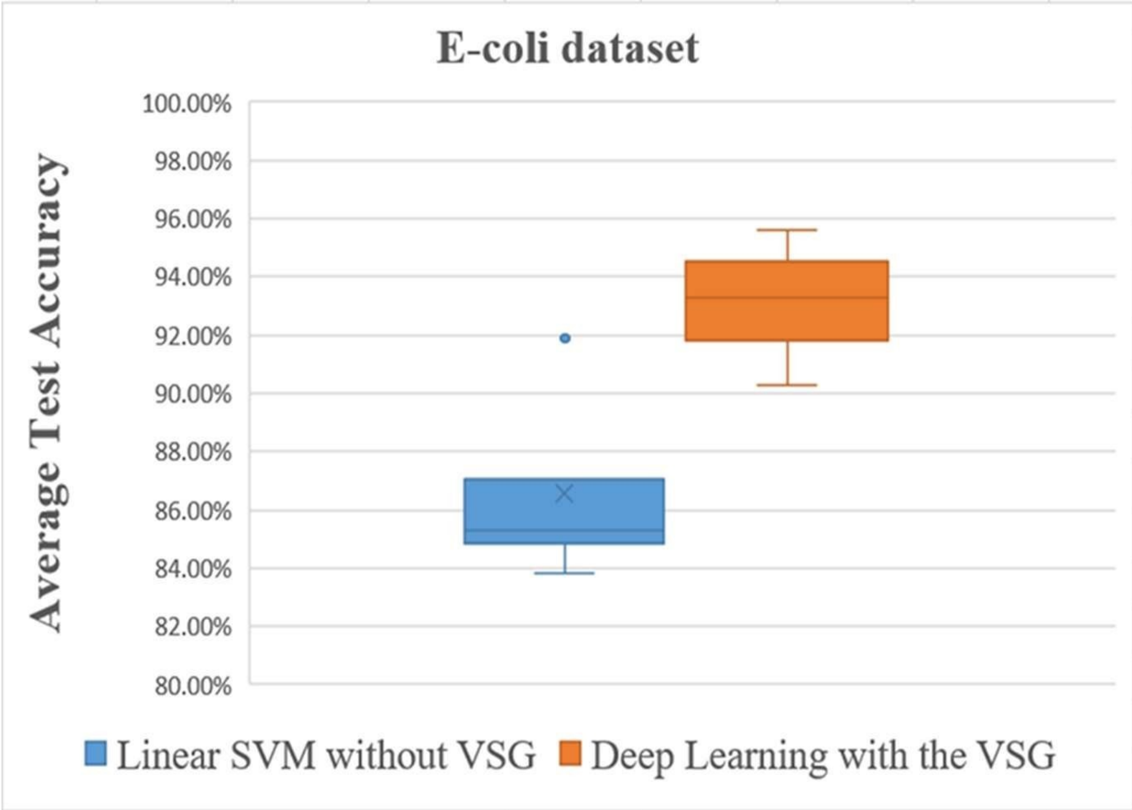


Figure 4.14 Overall comparisons of experimental results using the E-coli dataset.

The box plot in Figure 4.14 clearly shows that the present deep learning method with the proposed method exceeded in overall comparisons the linear SVM method using the E. coli dataset.

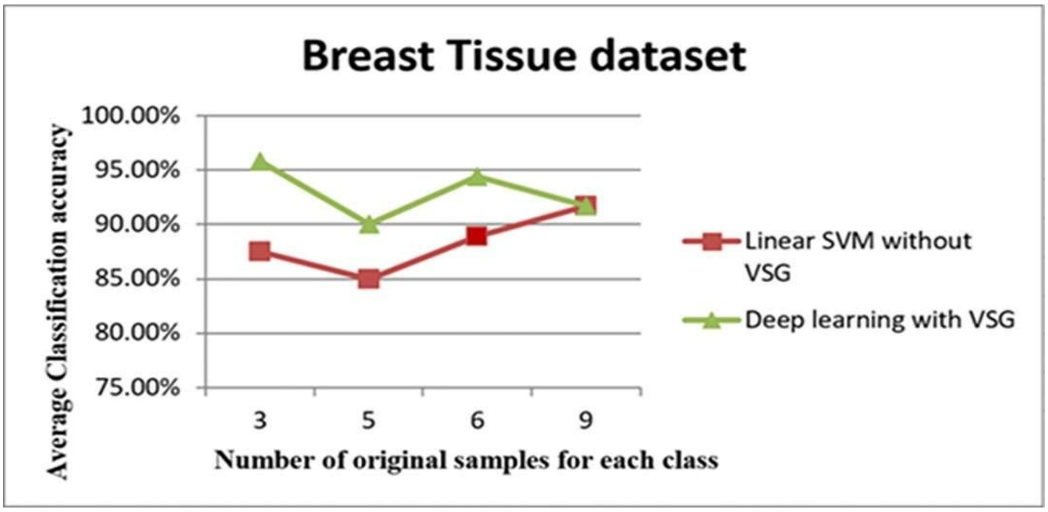


Figure 4.15 The trend of the average accuracy using the Breast Tissue dataset.

The line graph in Figure 4.15 shows the comparison between the performance of linear SVM without VSG and deep learning with VSG in the Breast Tissue dataset. The x-axis of this graph shows the original samples for each class that were used to generate the virtual sample in deep learning and the training sample for linear SVM, while the average of classification accuracy is the y-axis. The experiment of our method performed on the Breast Tissue dataset replicated the trend of the findings for the IRCCS Medea dataset and the E. coli dataset. Indeed, it is clear that deep learning with the proposed method outperformed the linear SVM method without VSG for the first three intervals considered.

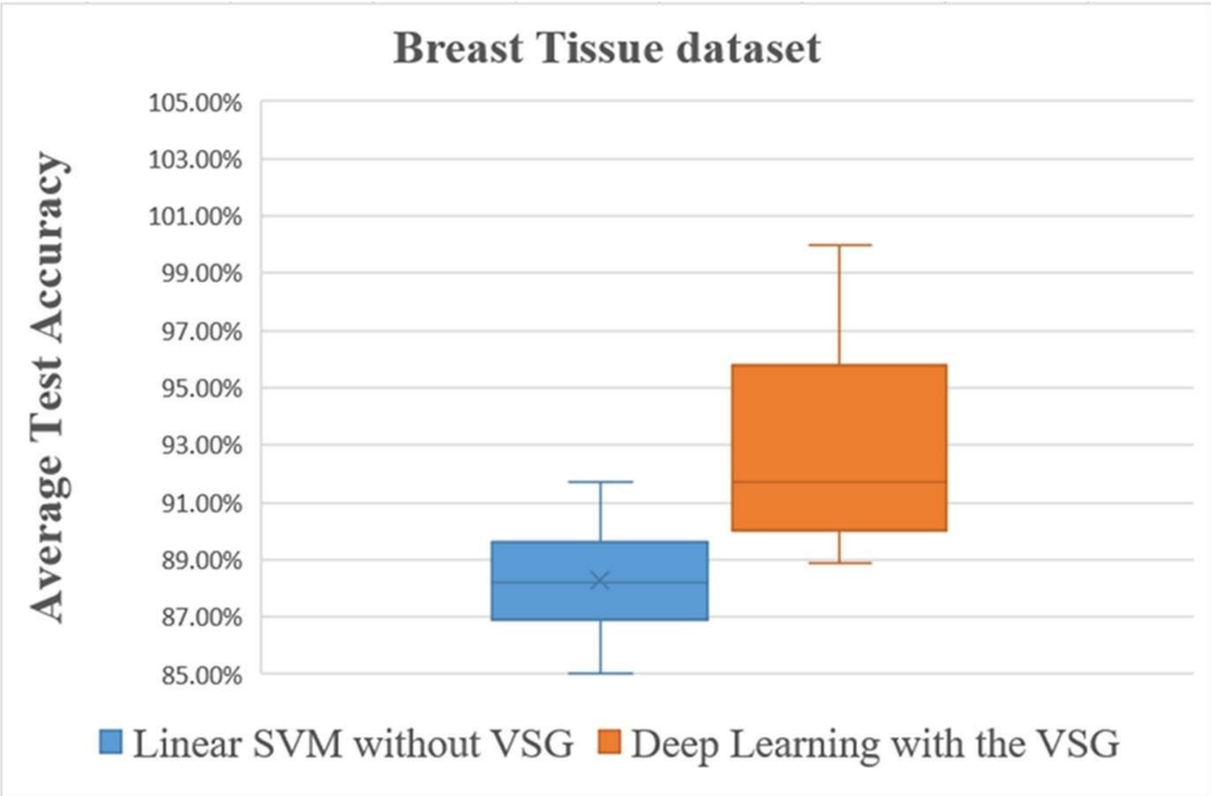


Figure 4.16 Overall comparisons of the experimental results using the Breast Tissue dataset.

The box plot in Figure 4.16 clearly shows that the present deep learning method with the proposed method exceeded in overall comparisons the linear SVM method using the Breast Tissue dataset.

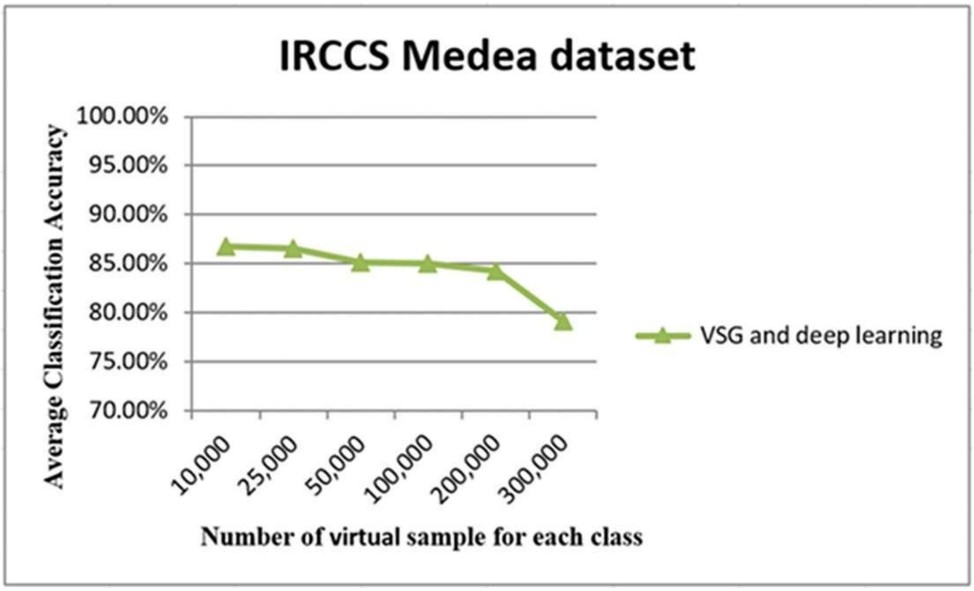


Figure 4.17 The accuracy using only the original five small training IRCCS Medea datasets.

The graph in Figure 4.17 shows the relationship between the number of virtual samples (five original samples were used to generate these samples) and the average of classification accuracy. The x-axis of this graph shows the number of virtual samples, while average accuracy appears on the y-axis. It may clearly be seen that average accuracy reached a peak with 25,000 samples. The accuracy performance remained reasonably stable until 200,000 samples; then, a loss of accuracy was observed for 300,000 samples.

4.5.4 The numerical example

In this section, we provide a numerical example to explain the proposed method, i.e., "the proposed method simulation." Five samples from both classes A and B are shown in Table 4.5 and Table 4.6, respectively. Then, the maximum and minimum values were extracted, and mean values were calculated from the first five features in both classes shown in Table 4.7- 4.9, respectively.

Table 4.5: Five samples from the first class (A).

Feature 1	Feature 2	Feature 3	Feature 4
5.1000	3.5000	1.4000	0.2000
4.9000	3.0000	1.4000	0.2000
4.7000	3.2000	1.3000	0.2000

4.6000	3.1000	1.5000	0.2000
5.000	3.6000	1.4000	0.2000

Table 4.6: Five samples from the second class (B).

Feature 1	Feature 2	Feature 3	Feature 4
7.0000	3.2000	4.7000	1.4000
6.4000	3.2000	4.5000	1.5000
6.9000	3.1000	4.9000	1.5000
5.5000	2.3000	4.0000	1.3000
6.5000	3.8000	4.6000	1.5000

Table 4.7: The maximum values extracted from the first five features.

	Feature 1	Feature 2	Feature 3	Feature 4
MAXA	5.1000	3.6000	1.5000	0.2000
MAXB	7	3.2000	4.9000	1.5000

Table 4.8: The minimum values extracted from the first five features.

	Feature 1	Feature 2	Feature 3	Feature 4
MINA	4.6000	3.0000	1.3000	0.2000
MINB	5.5000	2.3000	4.0000	1.3000

Table 4.9: The mean values calculated from the first five features.

	Feature 1	Feature 2	Feature 3	Feature 4
Mean A	4.8600	3.2800	1.4000	0.2000
Mean B	6.4600	2.9200	4.5400	1.4400

Features 1, 3, and 4 represented ideal cases, where we expanded the intervals and started to generate virtual random numbers based on a Gaussian distribution without any pre-processing, but Feature 2 was case H, so we performed a pre-processing before generating random numbers. In case H, to convert it to the ideal case, the MaxB or MinA would be changed depending on this simple comparison.

If (MeanA – MinA > MaxB - MeanB) ***{If the distance between point A and its features' average greater than the distance between point B and its features' average}***

Then

MinA = next position in the list, which is sorted in ascending order;

Else

MaxB = next position in the list, which is sorted in descending order;

End

The condition is false (3.28 – 3 > 3.2 - 2.92), so MaxB = 3.1;

Check that the case is still not the ideal case; it is a case H;

Check the same condition;

It is true now, so MinA = 3.1;

Check that the case is an ideal condition to expand the interval and start to generate virtual random numbers based on a Gaussian distribution as shown in Table 4.10 and Table 4.11.

Table 4.10: Ten virtual samples (A).

Feature 1	Feature 2	Feature 3	Feature 4
4.8856	3.7828	1.3874	0.2000
4.9425	3.0040	1.4145	0.2000
5.0047	3.4980	1.4130	0.2000
5.0954	3.4012	1.4648	0.2000
4.6168	3.0401	1.4256	0.2000
4.3748	3.3998	1.3600	0.2000
4.5446	3.5024	1.3004	0.2000
5.2189	3.5120	1.4902	0.2000
4.0010	3.5980	1.4533	0.2000
4.3178	3.5890	1.4503	0.2000

Table 4.11: Ten virtual samples (B).

Feature 1	Feature 2	Feature 3	Feature 4
5.7083	2.8643	4.4777	1.3378
6.0240	2.4625	4.2046	1.4321
5.7270	2.8160	4.6385	1.4882
6.2451	2.4472	4.1338	1.4951
6.7130	3.1154	4.5923	1.3216
6.4493	2.3696	4.5706	1.3358
6.526	2.6047	4.2064	1.4493
6.4594	2.8226	4.1640	1.3099
6.5940	2.7277	4.1497	1.3143
6.7898	3.0248	4.1346	1.3978

4.6 Conclusions and future extensions

Deep neural networks are successful learning tools for building nonlinear models; however, they display unstable performance when using small datasets. In order to solve this issue, the present work proposed a new technique to generate virtual samples, starting from the original small dataset, which can be added to the original samples to expand the training dataset significantly for machine learning. Thus, our method can produce meaningful virtual samples closely related to the original datasets in order to make the learning phase more stable and overcome the common limitations of the classification performance, such as the limited size of clinical sample data.

The newly-developed technique focused on binary classification. However, this technique can also be used for multi-class data to generate virtual samples. In the case of multi-class data, the only condition needed would be that intervals must not overlap. Apart from this, the remaining procedure would be the same as for binary classification.

As noted above, our method required not having overlaps between intervals. The system checked if the intervals had a direct ideal case (Figure 4.3), then the system started generating a virtual sample without any pre-processing. Otherwise, the system tried to get rid of overlaps if success expanded the interval range, and it would start to generate virtual samples between the known intervals. Otherwise, it would skip to the next features. Therefore, the novel technique was easy to apply and could help to make the learning stage more stable and enhance the classification performance.

The application of our method to the IRCCS Medea and UCI datasets showed that the present technique could significantly improve the classification accuracy in cases where the dataset had a limited size. More specifically, when applied to the IRCCS Medea dataset, our method augmented the classification accuracy from 84.9 [1] to 95%, 83.8%-93.9% for only three samples in each class for the E. coli dataset, and from 91.7%-100% for the Breast Tissue dataset.

These findings demonstrated that our technique not only offered high classification accuracy, but was also reliable and easy to apply (refer to Algorithms 1 and 2). The experiments reported in this study also showed that, given an appropriate number of the generated virtual samples, the generalisation efficiency of the classification on the new training set may be better than that of the original training set, and this agrees with many studies such as [279].

The best numbers for the original sample are best in these tables, for example (Tables 4.2 4.4) when the number of original samples is small, and the effect of the proposed algorithm is less effective when the original sample becomes larger. Future studies might delineate more specific matters in determining the best number for the original sample and the virtual sample in order to get maximum accuracy in terms of the results. In addition, the technique could be applied to a wide dataset to determine the strengths and limitations. These suggested directions could help to ensure that this important methodology is further refined and enhanced.

Chapter Five
Conclusion and Future Work

In this thesis, we have described the Ph.D. research that was conducted over the past four years, and the results we have achieved to date. We have built a completed novel system that diagnoses autism based on upper limb movements, in a child-friendly and effective environment. This system has also used inexpensive and highly available tools. In addition, this thesis focuses on providing a technique to deal with the small data size and this is based on augmented data from a small real dataset.

5.1 Summary and contributions

While the child was doing the required task, the system tracked and recorded the movements of the child's upper limb. The child-friendly and effective environment was achieved by employing augmented reality to design and create attractive virtual objects. Then, we used machine learning algorithms such as LDA to extract features from raw data, SVM, ELM, and Softmax to classify data collected in two different groups of children i.e. children with autism, and children without autism. This system allowed us to achieve remarkable accuracy in classifying autism based solely on the movements of a child’s upper limb.

The required data for the system testing has been collected from different sources; we gained the ethical approval number ETH18-2710 from the University of Technology Sydney, titled “Implementation of an Augmented Reality Game to Track Upper Limb Movement in Autistic Children.” In addition, this research was conducted in collaboration with the National Database for Autism Research (NDAR) in the USA, and the Scientific Institute IRCCS Eugenio Medea in Italy. These institutions provided access to the database regarding the kinematic analysis of upper-limb movement in children with autism and typically developing children.

Moreover, we have proposed a virtual sample generation algorithm to overcome the small clinical sample size problem. Results showed that our method had enhanced classification accuracy by using virtual samples for training the classifiers; these virtual samples were generated based on small clinical samples. The presented findings demonstrate the feasibility of using the proposed technique to improve classification performance even in cases of clinical samples that are of limited size. Therefore, our method represents a meaningful step forward in terms of pattern recognition methodology, particularly when applied to diagnostic classifications of neurodevelopmental disorders. Moreover, the proposed technique has proven its ability to be generalised by testing it with benchmark datasets such as the Breast Tissue dataset and Escherichia-coli dataset. The experimental outcomes for these benchmark datasets showed that the accuracy of the classification that used virtual samples was superior to the one that used original training data without virtual samples.

The experimental results in this Ph.D. research:

- Proved that upper-limb movements are useful for accurately classifying children with autism. It was investigated in our four papers, which have been published in SSCI 2016 [2], IRIS 2016 [3], HIS 2018 [4], and the *International Journal of Hybrid Intelligent Systems* 2019 [5].
- Determined which children task is most discriminating in the diagnosis of autism. This evaluative research has been published in ISKE 2017 [6].
- Revealed that the mechanisms that have been used in the system at each stage, play an important role in the results. Investigated in journal paper, which have

been published in the *International Journal of Hybrid Intelligent Systems* 2019 [5].

- Presented and evaluated previous studies in the use of augmented reality in the diagnosis and treatment of autistic children (has been accepted for publication in *Multimedia Tools and Applications Journal*).
- Used augmented reality to simulate a task creating a child-friendly environment (which have been published in ABEC [7] and a new paper has been accepted for publication in *Multimedia Tools and Applications Journal*).
- Achieved accurate measurements after tracking upper limb movements without any wearable sensors in a friendly manner (which have been published in ABEC [7] and a new paper has been accepted for publication in *Multimedia Tools and Applications Journal*).
- Showed that the deep neural networks can be used even if we have a small sample. It was investigated in journal paper, which have been published in *Algorithms Journal* [8].

The thesis work has endeavoured to tackle a real-life problem motivated by a collaboration with clinical researchers from the Al-Bwqaei Center and Scientific Institute IRCCS Eugenio Medea. We have designed a novel system to diagnose children with autism by measuring their upper limb movements using AR. The AR was used to create virtual objects, to encourage the children to move their hands and then record all of the required movements of the children by the Microsoft Kinect, which is potentially a low-cost solution. The system consists of three parts; an AR task, tracking movements program, and analysis of collected data.

In the AR part, the solution started by providing a customisable platform for autistic children by designing virtual objects that are controlled by a child's hand movements. This AR task project was created by using the latest trends in Human-Computer Interaction (HCI). Also, we did not randomly select the simulated task, we evaluated all tasks in previous studies to determine the best exercise and simulated the specific task.

In the tracking movements program part, it aims to measure the upper limb movements of autistic children based on the ability of Microsoft Kinect to represent human joints using 3D coordinates. Microsoft Kinect generates a massive amount of kinetic data. Thus, this data must be handled quickly and accurately, and that is exactly what we did, as shown in the previous chapters. Also, the tracking movements system should be an effective and child-friendly environment; and this was achieved based on the evaluations of the caregivers and the feedback of psychologists.

In the analysis part, the collected data was analysed by the machine learning algorithms. For example, Linear Discriminant Analysis (LDA) is used for extracting the features from raw data, Extreme Learning Machine (ELM), Support Vector Machine (SVM), and Softmax algorithms are used for classification. The analysis part of the new system improved the results of the data collected and analysed through previous studies and achieved excellent results in the new collected datasets.

The doctoral thesis work has led to valuable conclusions:

- Proved that autism diagnosis, based purely on the upper limb movement of a child, is possible. This conclusion has been investigated in our four studies, which have been published in SSCI 2016 [2], in IRIS 2016 [3], in HIS 2018 [4], and in the *International Journal of Hybrid Intelligent Systems* 2019 [5]. These studies are based on different datasets (The National Database for Autism Research (NDAR) in the USA, and Scientific Institute IRCCS Eugenio Medea in Italy). Furthermore, it has evaluated different tasks to understand which motion had the highest capacity for discrimination for autism. This evaluative research has been published in ISKE 2017 [6].

- Designed and implemented an augmented reality system that aims to measure the movements of children to provide a child-friendly environment. The system used AR to create virtual objects to encourage children to move their hands then it tracked the children's movements by the Microsoft Kinect. This is potentially a low-cost solution, and it is efficient as it does not require any wearable hardware sensors. This research has been published as a framework in ABEC 2018 [7] and it has been accepted for publication as a completed system paper to *Multimedia Tools and Applications Journal*.
- Used deep neural networks, despite the small sample size, and proposed a virtual sample generation algorithm to overcome the limitations of the finite sample size. The proposed algorithm works to improve classification performance significantly when working with small samples. The results showed that when virtual samples were generated based on small original samples, the accuracy of the autism classification was enhanced compared with traditional methods. This research has been published in the *Algorithms Journal* [8].

Important results were achieved and these are detailed below.

In chapter 3, the new system design considerations were covered as well as the key features; the appearance and the tracking part of the system were built and tested. In addition, this chapter showed the collaboration with the National Database for Autism Research (NDAR) in the USA, and the Scientific Institute IRCCS Eugenio Medea in Italy, both institutions provided access to the database on the kinematic analysis of upper-limb movement in children with autism and typically developing children. In relation to the NDRA datasets, through the means of our research, the dataset was for first time analysed by machine learning and categorised. The accuracy of the classification in the new system was 81.67%. Further, for the IRCCS dataset, the accuracy of classification in the new system was 93.80%. This was superior to the previous studies which had classified the same data, and the accuracy was 84.9%.

Moreover, in this chapter, ethical approval number ETH18-2710 was approved by the University of Technology Sydney, titled "Implementation of an Augmented Reality Game to Track Upper Limb Movement in Autistic Children." We have built a new integrated system that diagnoses autism based on upper limb movements in a child-friendly and effective environment. Furthermore, the system has excellent accuracy of up to 90%.

In chapter 4, the proposed VSG was applied and the results showed that our method enhanced diagnostic accuracy from 84%–95% using virtual samples generated based on five actual clinical samples. The present findings showed the feasibility of using the proposed technique to improve classification performance even in cases of clinical samples of limited size. Accounting for concerns relating to small sample sizes, our method represented a meaningful step forward in terms of pattern recognition methodology, particularly when it was applied to diagnostic classifications of neurodevelopmental disorders. In addition, the proposed technique has been tested with other available benchmark datasets. The experimental outcomes showed that the accuracy of the classification that used virtual samples was superior to the one that used original training data without virtual samples and the improvements reached a level of around 10%.

Although these conclusions constitute state of the art developments on these topics, we believe that there are still significant unresolved challenges ahead. Should we be allowed to continue this work, two natural extensions would be refining the AR system according to specialist feedback and applying the virtual sample generation to different fields.

5.2 Future work

There are many opportinities to follow up on the thesis work, including the following directions:

- Improving the new autism diagnostic system based on feedback from the children's teachers because they evaluated our system during the experiments; this will serve as a guide to assist us to know how the teachers and the children perceived the performance of the new system.
- Helping families diagnose autism at home by training adult family members on the system for both components hardware and software, such as the system settings and system installation; this is important for the effective management of autism. Although there is no current treatment to prevent autism, early detection of autism can lead to an excellent outcome. The system can diagnose autism with accuracy around 90%, which can help families to visit a health professional to prove the diagnosis, and start interventions and treatment sooner.
- Evaluate our new AR system on a range of children within the targeted group. We need to assess the AR system manipulation tasks in terms of their effectiveness in diagnosing autism and improving the lives of autistic children.
- Determining the best number virtual sample and the original sample in order to get maximum accuracy in terms of the results and find the relationship between them.

- Generalize our algorithm to be applied to a broad range of problems not only binary datasets by upgrading the algorithm and increase the parameters that describe the features.
- Further experiments are required for adapting our VSG algorithm preparation of the model to serve as a generative adversarial network (GAN).
- Finally, applying the VSG algorithm on wide types of benchmark databases for more generalisation that will ultimately lead to higher quality and more utilisation in the future for the proposed algorithm.

Bibliography

[1] A. Crippa *et al.*, "Use of machine learning to identify children with autism and their motor abnormalities," *Journal of autism and developmental disorders,* vol. 45, no. 7, pp. 2146-2156, 2015.

[2] M. Wedyan and A. Al-Jumaily, "Upper limb motor coordination based early diagnosis in high risk subjects for Autism," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, Athens, Greece, 6-9 December 2016: IEEE, pp. 1-8.

[3] M. Wedyan and A. Al-Jumaily, "Early diagnosis autism based on upper limb motor coordination in high risk subjects for autism," in *2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS)*, Tokyo, Japan, 17–20 December 2016: IEEE, pp. 13-18.

[4] M. Wedyan, A. Al-Jumaily, and A. Crippa, "Early Diagnose of Autism Spectrum Disorder Using Machine Learning Based on Simple Upper Limb Movements," in *International Conference on Hybrid Intelligent Systems*, Porto, Portugal, 13 - 15 December 2018: Springer, pp. 491-500.

[5] M. Wedyan, A. Al-Jumaily, and A. Crippa, "Using machine learning to perform early diagnosis of autism spectrum disorder based on simple upper limb movements," *International Journal of Hybrid Intelligent Systems,* vol. 15, no. 4, pp. 1-12, 2019.

[6] M. Wedyan and A. Al-Jumaily, "An investigation of upper limb motor task based discriminate for high risk autism," in *2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, Nanjing, China, 24-26 November 2017: IEEE, pp. 1-6.

[7] W. Mohammad, A. Ahmed, and A.-J. Adel, "Design and Implementation of an Augmented Reality Game to Diagnose Autism," in *The Australian Biomedical Engineering Conference (ABEC)*, Australia, October 7-10 2018, p. 4.

[8] M. Wedyan, A. Crippa, and A. Al-Jumaily, "A Novel Virtual Sample Generation Method to Overcome the Small Sample Size Problem in Computer Aided Medical Diagnosing," *Algorithms,* vol. 12, no. 8, pp. 160-185, 2019.

[9] Y. Tian, X. Meng, D. Tao, D. Liu, and C. Feng, "Upper limb motion tracking with the integration of IMU and Kinect," *Neurocomputing,* vol. 159, pp. 207-218, 2015.

[10] J. Allen, R. Balfour, R. Bell, and M. Marmot, "Social determinants of mental health," *International review of psychiatry,* vol. 26, no. 4, pp. 392-407, 2014.

[11] H. S. S. Yee, "Mobile technology for children with Autism Spectrum Disorder: Major trends and issues," in *IEEE Symposium on E-Learning, E-Management and E-Services, IS3e*, Kuala Lumpur, Malaysia, 21-24 October 2012: IEEE, pp. 1-5.

[12] S. Veeraraghavan and K. Srinivasan, "Exploration of autism expert systems," in *Fourth International Conference on Information Technology (ITNG'07)*, Las Vegas, Nevada, USA, 2 - 4 April 2007: IEEE, pp. 261-264.

[13] M. Mythili and A. Shanavas, "A Study on Autism Spectrum Disorders using Classification Techniques," *International Journal of Soft Computing and Engineering (IJSCE),* vol. 4, no. 5, pp. 89-91, 2014.

[14] J. Munson and P. Pasqual, "Using technology in autism research: the promise and the perils," *Computer,* vol. 45, no. 6, pp. 89-91, 2012.

[15] Y. Cai, N. K. Chia, D. Thalmann, N. K. Kee, J. Zheng, and N. M. Thalmann, "Design and development of a virtual dolphinarium for children with autism," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 21, no. 2, pp. 208-217, 2013.

[16] M. Wang and D. Reid, "Virtual reality in pediatric neurorehabilitation: attention deficit hyperactivity disorder, autism and cerebral palsy," *Neuroepidemiology,* vol. 36, no. 1, pp. 2-18, 2010.

[17] D. Mazzei *et al.*, "The face of autism," in *19th RO-MAN*, Viareggio, Italy, 13-15 September 2010: IEEE, pp. 791-796.

[18] E. A. Alsaggaf and S. S. Baaisharah, "Directions of Autism Diagnosis by Electroencephalogram Based brain Computer Interface: A Review," *Life Science Journal,* vol. 11, no. 6, pp. 298–304, 2014.

[19] M. Knapp, R. Romeo, and J. Beecham, *The economic consequences of autism in the UK* (Foundation for People with Learning Disabilities). London: Economics of Mental Health, King's College, 2007, pp. 1–27.

[20] M. Knapp, R. Romeo, and J. Beecham, "Economic cost of autism in the UK," *Autism,* vol. 13, no. 3, pp. 317-336, 2009.

[21] K. Järbrink, "The economic consequences of autistic spectrum disorder among children in a Swedish municipality," *Autism,* vol. 11, no. 5, pp. 453-463, 2007.

[22] A. V. Buescher, Z. Cidav, M. Knapp, and D. S. Mandell, "Costs of autism spectrum disorders in the United Kingdom and the United States," *JAMA pediatrics,* vol. 168, no. 8, pp. 721-728, 2014.

[23] Z. Cidav, S. C. Marcus, and D. S. Mandell, "Implications of childhood autism for parental employment and earnings," *Pediatrics,* vol. 129, no. 4, pp. 617-623, 2012.

[24] T. A. Lavelle, M. C. Weinstein, J. P. Newhouse, K. Munir, K. A. Kuhlthau, and L. A. Prosser, "Economic burden of childhood autism spectrum disorders," *Pediatrics,* vol. 133, no. 3, pp. 520-529, 2014.

[25] R. L. Mendoza, "The economics of autism in Egypt," *American Journal of Economics and Business Administration,* vol. 2, no. 1, pp. 12-19, 2010.

[26] D. L. Sharpe and D. L. Baker, M.-R. Mohammadi, Ed. *The financial side of autism: Private and public costs* (A comprehensive book on autism spectrum disorders). InTeach, 2011.

[27] M. L. Ganz, "The lifetime distribution of the incremental societal costs of autism," *Archives of pediatrics & adolescent medicine,* vol. 161, no. 4, pp. 343-349, 2007.

[28] L. Roth, "Autism spectrum disorder, Briefing Paper No. 5/2013, NSW Parliamentary Research Service," ed, 2014, pp. 1–40.

[29] C. Horlin, M. Falkmer, R. Parsons, M. A. Albrecht, and T. Falkmer, "The cost of autism spectrum disorders," *PloS one,* vol. 9, no. 9, pp. e106552 (1-9), 2014.

[30] K. Järbrink, P. McCrone, E. Fombonne, H. Zandén, and M. Knapp, "Cost-impact of young adults with high-functioning autistic spectrum disorder," *Research in developmental disabilities,* vol. 28, no. 1, pp. 94-104, 2007.

[31] C. Dudley and J. Emery, "The value of caregiver time: Costs of support and care for individuals living with autism spectrum disorder," *SPP Research Paper,* vol. 7, no. 1, pp. 1–48, 2014.

[32] K. Dillenburger, L. McKerr, and J.-A. Jordan, "Lost in translation: public policies, evidence-based practice, and Autism Spectrum Disorder," *International Journal of Disability, Development and Education,* vol. 61, no. 2, pp. 134-151, 2014.

[33] C. Fountain, M. D. King, and P. S. Bearman, "Age of diagnosis for autism: individual and community factors across 10 birth cohorts," *Journal of Epidemiology and Community Health,* vol. 65, no. 6, pp. 503-510, 2011.

[34] M. King and P. Bearman, "Diagnostic change and the increased prevalence of autism," *International journal of epidemiology,* vol. 38, no. 5, pp. 1224-1234, 2009.

[35] P. I. Markowitz, "Autism in a child with congenital cytomegalovirus infection," *Journal of autism and developmental disorders,* vol. 13, no. 3, pp. 249-253, 1983.

[36] M. Sigman, S. J. Spence, and A. T. Wang, "Autism from Developmental and Neuropsychological Perspectives," *Annual Review of Clinical Psychology,* vol. 2, no. 1, pp. 327-355, 2006/04/01 2006, doi: 10.1146/annurev.clinpsy.2.022305.095210.

[37] R. C. M. Philip, "Emotion processing in autism spectrum disorder," Doctoral thesis, University of Edinburgh, Edinburgh, Scotland, 2009. [Online]. Available: https://era.ed.ac.uk/bitstream/handle/1842/4216/Philip2009.pdf?sequence=2&isAllowed=y

[38] L. Zwaigenbaum, S. Bryson, T. Rogers, W. Roberts, J. Brian, and P. Szatmari, "Behavioral manifestations of autism in the first year of life," *International journal of developmental neuroscience,* vol. 23, no. 2, pp. 143-152, 2005.

[39] G. Dawson, J. Osterling, A. N. Meltzoff, and P. Kuhl, "Case study of the development of an infant with autism from birth to two years of age," *Journal of Applied Developmental Psychology,* vol. 21, no. 3, pp. 299-313, 2000.

[40] P. J. Krantz and L. E. McClannahan, "Social interaction skills for children with autism: A script-fading procedure for beginning readers," *Journal of applied behavior analysis,* vol. 31, no. 2, pp. 191-202, 1998.

[41] J. Hashemi *et al.*, "A computer vision approach for the assessment of autism-related behavioral markers," in *International Conference on Development and Learning and Epigenetic Robotics (ICDL,2012)*, San Diego, California, USA, 7-9 November 2012: IEEE, pp. 1-7.

[42] C. P. Johnson and S. M. Myers, "Identification and evaluation of children with autism spectrum disorders," *Pediatrics,* vol. 120, no. 5, pp. 1183-1215, 2007.

[43] L. K. Koegel, R. L. Koegel, K. Ashbaugh, and J. Bradshaw, "The importance of early identification and intervention for children with or at risk for autism

spectrum disorders," *International journal of speech-language pathology,* vol. 16, no. 1, pp. 50-56, 2014.

[44] E. Fernell, M. A. Eriksson, and C. Gillberg, "Early diagnosis of autism and impact on prognosis: a narrative review," *Clinical epidemiology,* vol. 5, no. 1, pp. 33-43, 2013.

[45] N. Aresti-Bartolome and B. Garcia-Zapirain, "Technologies as support tools for persons with autistic spectrum disorder: a systematic review," *International journal of environmental research and public health,* vol. 11, no. 8, pp. 7767-7802, 2014.

[46] M. Tentori, L. Escobedo, and G. Balderas, "A smart Environment for children with autism," *Pervasive Computing, IEEE,* vol. 14, no. 2, pp. 42-50, 2015.

[47] E. Quintana, C. Ibarra, L. Escobedo, M. Tentori, and J. Favela, "Object and gesture recognition to assist children with autism during the discrimination training," in *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*, Buenos Aires, Argentina, 3-6 September 2012: Springer, pp. 877-884.

[48] R. T. Azuma, "A survey of augmented reality," *Presence: Teleoperators and virtual environments,* vol. 6, no. 4, pp. 355-385, 1997.

[49] L. Boccanfuso and J. M. O’kane, "Adaptive robot design with hand and face tracking for use in autism therapy," in *International conference on Social Robotics*, Singapore, Springer, November 23-24 2010: Springer, pp. 265-274.

[50] R. A. Russell, G. Taylor, L. Kleeman, and A. H. Purnamadjaja, "Multi-sensory synergies in humanoid robotics," *International Journal of Humanoid Robotics,* vol. 1, no. 02, pp. 289-314, 2004.

[51] B. Scassellati, H. Admoni, and M. Matarić, "Robots for use in autism research," *Annual review of biomedical engineering,* vol. 14, pp. 275-294, 2012.

[52] J. Wainer, K. Dautenhahn, B. Robins, and F. Amirabdollahian, "Collaborating with Kaspar: Using an autonomous humanoid robot to foster cooperative dyadic play among children with autism," in *10th IEEE RAS International Conference on Humanoid Robots*, Nashville, TN, USA, 6-8 December 2010: IEEE, pp. 631-638.

[53] A. Billard, B. Robins, J. Nadel, and K. Dautenhahn, "Building robota, a mini-humanoid robot for the rehabilitation of children with autism," *Assistive Technology,* vol. 19, no. 1, pp. 37-49, 2007.

[54] A. M. Cook, K. Adams, J. Volden, N. Harbottle, and C. Harbottle, "Using Lego robots to estimate cognitive ability in children who have severe physical disabilities," *Disability and Rehabilitation: Assistive Technology,* vol. 6, no. 4, pp. 338-346, 2011.

[55] A. Duquette, H. Mercier, and F. Michaud, "Investigating the use of a mobile robotic toy as an imitation agent for children with autism," in *Proceedings International Conference on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems*, Paris, France, September 20-22 2006, pp. 167-168.

[56] D. J. Ricks, M. B. Colton, and M. A. Goodrich, "Design and evaluation of a clinical upper-body humanoid robot for autism therapy," in *In Proceedings of the 2010 International Conference on Applied Bionics and Biomechanics*, Venice, Italy, 14-16 October 2010, pp. 14–16.

[57] N. Giullian, D. Ricks, A. Atherton, M. Colton, M. Goodrich, and B. Brinton, "Detailed requirements for robots in autism therapy," in *Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on*, Istanbul, Turkey, 10-13 October 2010: IEEE, pp. 2595-2602.

[58] J. Hailpern, K. Karahalios, L. DeThorne, and J. Halle, "Vocsyl: Visualizing syllable production for children with ASD and speech delays," in *Proceedings of the 12th international ACM SIGACCESS conference on Computers and accessibility*, Orlando, Florida, USA, 25 - 27 October 2010: ACM, pp. 297-298.

[59] Z. Bai, A. F. Blackwell, and G. Coulouris, "Using Augmented Reality to Elicit Pretend Play for Children with Autism," *Visualization and Computer Graphics, IEEE Transactions on,* vol. 21, no. 5, pp. 598-610, 2015.

[60] J. Brandão, P. Cunha, J. Vasconcelos, V. Carvalho, and F. Soares, "An Augmented Reality GameBook for Children with Autism Spectrum Disorders," in *The International Conference on E-Learning in the Workplace 2015*, New York, United States of America, June 10-12 2015, pp. 1–6.

[61] N. Lakshmiprabha, A. Santos, D. Mladenov, and O. Beltramello, "[Poster] An augmented and virtual reality system for training autistic children," in

International Symposium on Mixed and Augmented Reality (ISMAR), Munich, Germany, 10-12 September 2014: IEEE, pp. 277-278.

[62] S. Radhakrishnan, "Mobile augmented reality in modern libraries: Prospects and challenges," *Indian Journal of Science,* vol. 21, no. 73, pp. 385-388, 2015.

[63] K. E. Ringland, R. Zalapa, M. Neal, L. Escobedo, M. Tentori, and G. R. Hayes, "SensoryPaint: a multimodal sensory intervention for children with neurodevelopmental disorders," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Seattle, WA, USA, 13 - 17 September 2014: ACM, pp. 873-884.

[64] J. Greczek, E. Kaszubski, A. Atrash, and M. Matarić, "Graded cueing feedback in robot-mediated imitation practice for children with autism spectrum disorders," in *The 23rd IEEE international symposium on robot and human interactive communication*, Edinburgh, UK, 25-29 August 2014: IEEE, pp. 561-566.

[65] HCII, "The Human-Computer Interaction Institute," ed: Scaffolding Science Achievement in a Culturally Diverse Classroom: Bridging the Gap with Virtual Peers, 2014.

[66] R. Azuma, Y. Baillot, R. Behringer, S. Feiner, S. Julier, and B. MacIntyre, "Recent advances in augmented reality," *Computer Graphics and Applications, IEEE,* vol. 21, no. 6, pp. 34-47, 2001.

[67] S. K. Bhatt, N. I. D. Leon, and A. Al, "Augmented Reality Game Therapy for Children with Autism Spectrum Disorder," *International Journal on Smart Sensing and Intelligent Systems,* vol. 7, no. 2, pp. 519–536, MARCH 2014 2014.

[68] M. Dunleavy and C. Dede, "Augmented reality teaching and learning," in *Handbook of research on educational communications and technology*. New York, NY: Springer, 2014, pp. 735-745.

[69] L. Escobedo, M. Tentori, E. Quintana, J. Favela, and D. Garcia-Rosas, "Using augmented reality to help children with autism stay focused," *Pervasive Computing, IEEE,* vol. 13, no. 1, pp. 38-46, 2014.

[70] O. Hugues, P. Fuchs, and O. Nannipieri, "New augmented reality taxonomy: Technologies and features of augmented environment," in *Handbook of augmented reality*. New York, NY: Springer, 2011, pp. 47-63.

[71] F. Liarokapis and E. F. Anderson, "Using augmented reality as a medium to assist teaching in higher education," in *Eurographics 2010*, Norrköping, Sweden, 3-7 MAY 2010: Eurographics Association, pp. 9–16.

[72] S. D. M.Sowmya sree, P.Sindhusha, "Augmented Reality," *International Journal of Scientific & Engineering Research,* vol. 4, no. 9, pp. 1469–1474, September 2013.

[73] S. Yuen, G. Yaoyuneyong, and E. Johnson, "Augmented reality: An overview and five directions for AR in education," *Journal of Educational Technology Development and Exchange,* vol. 4, no. 1, pp. 119-140, 2011.

[74] Y. M. Aung and A. Al-Jumaily, "AR based upper limb rehabilitation system," in *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, Rome, Italy, 24 - 27 June 2012: IEEE, pp. 213-218.

[75] Y. M. Aung, A. Al-Jumaily, and K. Anam, "A novel upper limb rehabilitation system with self-driven virtual arm illusion," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, Illinois, USA, August 26-30 2014: IEEE, pp. 3614-3617.

[76] D. McMahon, D. F. Cihak, and R. Wright, "Augmented reality as a navigation tool to employment opportunities for postsecondary education students with intellectual disabilities and autism," *Journal of Research on Technology in Education,* vol. 47, no. 3, pp. 157-172, 2015.

[77] D. Lo, P. R. Mendonça, and A. Hopper, "TRIP: A low-cost vision-based location system for ubiquitous computing," *Personal and Ubiquitous Computing,* vol. 6, no. 3, pp. 206-219, 2002.

[78] I. Herbst, A.-K. Braun, R. McCall, and W. Broll, "TimeWarp: interactive time travel with a mobile mixed reality game," in *Proceedings of the 10th international conference on Human computer interaction with mobile devices and services*, Amsterdam, The Netherlands, 02 - 05 September 2008: ACM, pp. 235-244.

[79] V. T. Phan and S. Y. Choo, "Interior design in augmented reality environment," *International Journal of Computer Applications,* vol. 5, no. 5, pp. 16–21, 2010.

[80] N. Raajan *et al.*, "Augmented reality based virtual reality," *Procedia Engineering,* vol. 38, pp. 1559-1565, 2012.

[81] P. Milgram, H. Takemura, A. Utsumi, and F. Kishino, "Augmented reality: A class of displays on the reality-virtuality continuum," in *Photonics for industrial applications*, Boston, MA, United States, 21 December 1995, vol. 2351: International Society for Optics and Photonics, pp. 282-293.

[82] A. Tang, F. Biocca, and L. Lim, "Comparing differences in presence during social interaction in augmented reality versus virtual reality environments: An exploratory study," in *7th Annual International Workshop on Presence (PRESENCE 2004)*, Valencia, Spain, 13-15 October 2004, pp. 204-208.

[83] J. Carmigniani and B. Furht, "Augmented reality: an overview," in *Handbook of augmented reality*. New York, NY: Springer, 2011, pp. 3-46.

[84] W. E. Mackay, "Augmented reality: linking real and virtual worlds: a new paradigm for interacting with computers," in *Proceedings of the working conference on Advanced visual interfaces*, L'Aquila, Italy, 25 - 27 May 1998: ACM, pp. 13-21.

[85] K. Lee, "Augmented reality in education and training," *TechTrends,* vol. 56, no. 2, pp. 13-21, 2012.

[86] Y. M. Aung and A. Al-Jumaily, "sEMG based ANN for shoulder angle prediction," *Procedia Engineering,* vol. 41, pp. 1009-1015, 2012.

[87] O. Bimber and R. Raskar, *Spatial augmented reality: merging real and virtual worlds*. CRC Press, 2005.

[88] M. Mekni and A. Lemieux, "Augmented reality: Applications, challenges and future trends," in *Applied Computational Science: Proceedings of the 13th International Conference on Applied Computer and Applied Computational Science (ACACOS '14)*, Kuala Lumpur, Malaysia, 23-25 April 2014, pp. 205–214.

[89] C.-Y. Lin *et al.*, "Augmented reality in educational activities for children with disabilities," *Displays,* vol. 42, pp. 51–54, 2015, doi: http://dx.doi.org/10.1016/j.displa.2015.02.004.

[90] Z. Bai, "Augmenting imagination for children with autism," in *Proceedings of the 11th International Conference on Interaction Design and Children*, Bremen, Germany, June 12 - 15 2012: ACM, pp. 327-330.

[91] H.-K. Wu, S. W.-Y. Lee, H.-Y. Chang, and J.-C. Liang, "Current status, opportunities and challenges of augmented reality in education," *Computers & Education,* vol. 62, pp. 41-49, 2013.

[92] M. Akçayır, G. Akçayır, H. M. Pektaş, and M. A. Ocak, "Augmented reality in science laboratories: The effects of augmented reality on university students' laboratory skills and attitudes toward science laboratories," *Computers in Human Behavior,* vol. 57, pp. 334-342, 2016.

[93] A. E. Yantac, D. Çorlu, M. Fjeld, and A. Kunz, "Exploring Diminished Reality (DR) Spaces to Augment the Attention of Individuals with Autism," in *Proceedings of the 2015 IEEE International Symposium on Mixed and Augmented Reality Workshops (ISMARW)*, Fukuoka, Japan, 29 September - 03 October 2015: IEEE, pp. 68-73.

[94] Z. Bai, A. Blackwell, and G. Coulouris, "Making Pretense Visible and Graspable: An augmented reality approach to promote pretend play," in *Mixed and Augmented Reality (ISMAR), 2012 IEEE International Symposium on*, Atlanta, GA, USA, November 5-8 2012: IEEE, pp. 267-268.

[95] L. Escobedo *et al.*, "MOSOCO: a mobile assistive tool to support children with autism practicing social skills in real-life situations," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Austin, Texas, USA, 05 - 10 May 2012: ACM, pp. 2589-2598.

[96] C.-H. Chen, I.-J. Lee, and L.-Y. Lin, "Augmented reality-based self-facial modeling to promote the emotional expression and social skills of adolescents with autism spectrum disorders," *Research in developmental disabilities,* vol. 36, pp. 396-403, 2015.

[97] D. D. McMahon, C. C. Smith, D. F. Cihak, R. Wright, and M. M. Gibbons, "Effects of Digital Navigation Aids on Adults With Intellectual Disabilities Comparison of Paper Map, Google Maps, and Augmented Reality," *Journal of Special Education Technology,* vol. 30, no. 3, pp. 157-165, 2015.

[98] C.-H. Chen, I.-J. Lee, and L.-Y. Lin, "Augmented reality-based video-modeling storybook of nonverbal facial cues for children with autism spectrum disorder to improve their perceptions and judgments of facial expressions and emotions," *Computers in Human Behavior,* vol. 55, pp. 477-485, 2016.

[99] D. D. McMahon, D. F. Cihak, R. E. Wright, and S. M. Bell, "Augmented Reality for Teaching Science Vocabulary to Postsecondary Education Students With Intellectual Disabilities and Autism," *Journal of Research on Technology in Education,* vol. 48, no. 1, pp. 38-56, 2016.

[100] P. Cunha, J. Brandão, J. Vasconcelos, F. Soares, and V. Carvalho, "Augmented reality for cognitive and social skills improvement in children with ASD," in *13th International Conference on Remote Engineering and Virtual Instrumentation (REV)*, Madrid, Spain, 24-26 February 2016: IEEE, pp. 334-335.

[101] A. J. Vullamparthi, S. C. B. Nelaturu, D. D. Mallaya, and S. Chandrasekhar, "Assistive Learning for Children with Autism Using Augmented Reality," in *2013 IEEE Fifth International Conference on Technology for Education (T4E)*, Kharagpur, India, 18 - 20 December 2013: IEEE, pp. 43-46.

[102] X. Casas, G. Herrera, I. Coma, and M. Fernández, "A Kinect-based Augmented Reality System for Individuals with Autism Spectrum Disorders," in *GRAPP/IVAPP*, Rome, Italy, February 24-26 2012, pp. 440-446.

[103] J. Favela, J. Kaye, M. Skubic, M. Rantz, and M. Tentori, "Living Labs for Pervasive Healthcare Research," *Pervasive Computing, IEEE,* vol. 14, no. 2, pp. 86-89, 2015.

[104] G. Herrera *et al.*, "Pictogram Room: Natural Interaction Technologies to Aid in the Development of Children with Autism," *Annuary of Clinical and Health Psychology,* vol. 8, no. 2012, pp. 39-44, 2012.

[105] E. Richard, V. Billaudeau, P. Richard, and G. Gaudin, "Augmented reality for rehabilitation of cognitive disabled children: A preliminary study," in *Virtual Rehabilitation, 2007*, Venice, Italy, 27-29 September 2007: IEEE, pp. 102-108.

[106] D. F. Cihak, E. J. Moore, R. E. Wright, D. D. McMahon, M. M. Gibbons, and C. Smith, "Evaluating augmented reality to complete a chain task for elementary students with autism," *Journal of Special Education Technology,* vol. 31, no. 2, pp. 99-108, 2016.

[107] M. El-Seoud, O. Halabi, and V. Geroimenko, "Assisting Individuals with Autism and Cognitive Disorders: An Augmented Reality based Framework," *International Journal of Online Engineering,* vol. 15, no. 4, pp. 28–39, 2019.

[108] G. Lorenzo, M. Gómez-Puerta, G. Arráez-Vera, and A. Lorenzo-Lledó, "Preliminary study of augmented reality as an instrument for improvement of

social skills in children with autism spectrum disorder," *Education and Information Technologies,* vol. 24, no. 1, pp. 181-204, 2019.

[109] T. Y. Tang, J. Xu, and P. Winoto, "Automatic Object Recognition in a Light-Weight Augmented Reality-based Vocabulary Learning Application for Children with Autism," in *Proceedings of the 2019 3rd International Conference on Innovation in Artificial Intelligence*, Suzhou, China, 15 - 18 March 2019: ACM, pp. 65-68.

[110] R. Liu, J. P. Salisbury, A. Vahabzadeh, and N. T. Sahin, "Feasibility of an autism-focused augmented reality smartglasses system for social communication and behavioral coaching," *Frontiers in pediatrics,* vol. 5, p. 145, 2017.

[111] N. T. Sahin, R. Abdus-Sabur, N. U. Keshav, R. Liu, J. P. Salisbury, and A. Vahabzadeh, "Augmented Reality Intervention for Social Communication in Autism in a School Classroom: Rated by Teachers and Parents as Effective and Usable in a Controlled, Longitudinal Pilot Study," in *PsyArXiv*, ed, 2018, pp. 1–10.

[112] N. Sahin, N. Keshav, J. Salisbury, and A. Vahabzadeh, "Safety and lack of negative effects of wearable augmented-reality social communication aid for children and adults with autism," *Journal of clinical medicine,* vol. 7, no. 8, pp. 188-205, 2018.

[113] S. Baron-Cohen, "Theory of mind in normal development and autism," *Prisme,* vol. 34, no. 1, pp. 74–183, 2001.

[114] P. Wolfberg, K. Bottema-Beutel, and M. DeWitt, "Including children with autism in social and imaginary play with typical peers: Integrated play groups model," *American Journal of Play,* vol. 5, no. 1, pp. 55-80, 2012.

[115] J. Boucher and P. Wolfberg, "Editorial: Aims and design of the special issue," *Autism,* vol. 7, pp. 339–346, 2003.

[116] H. E. Pashler and S. Sutherland, *The psychology of attention*. Cambridge, MA: MIT press Cambridge, MA, 1998.

[117] C. Ames and S. Fletcher-Watson, "A review of methods in the study of attention in autism," *Developmental Review,* vol. 30, no. 1, pp. 52-73, 2010.

[118] P. Michel, "The use of technology in the study, diagnosis and treatment of autism," in *Final term Paper for CSC350: Autism and Associated Developmental Disorders*, ed, 2004, pp. 1–26.

[119] F. M. Gresham and S. N. Elliott, "The relationship between adaptive behavior and social skills issues in definition and assessment," *The Journal of special education,* vol. 21, no. 1, pp. 167-181, 1987.

[120] M. J. Weiss and S. L. Harris, "Teaching social skills to people with autism," *Behavior modification,* vol. 25, no. 5, pp. 785-802, 2001.

[121] K. R. Scherer, "Toward a dynamic theory of emotion," *Geneva studies in Emotion,* vol. 1, pp. 1-96, 1987.

[122] J. Prinz, "Which emotions are basic," *Emotion, evolution, and rationality, Oxford University Press,* vol. 69, pp. 1–288, 2004.

[123] C. Ashwin, E. Chapman, L. Colle, and S. Baron-Cohen, "Impaired recognition of negative basic emotions in autism: A test of the amygdala theory," *Social neuroscience,* vol. 1, no. 3-4, pp. 349-363, 2006.

[124] J. Hadwin, S. Baron-Ohen, P. Howlin, and K. Hill, "Can we teach children with autism to understand emotions, belief, or pretence?," *Development and Psychopathology,* vol. 8, no. 2, pp. 345-366, 1996.

[125] H. A. Karimi, *Introduction to Navigation* (Universal Navigation on Smartphones). Pittsburgh, Pennsylvania, USA: Springer Science & Business Media, 2011, pp. 1-16.

[126] N. Mieke, "An Overview of Augmented Reality Technologies," in *11 th Research Seminar Series Workshop*, Bradford, UK, 18 April 2012: University of Bradford, pp. 142-147. [Online]. Available: https://bradscholars.brad.ac.uk/. [Online]. Available: https://bradscholars.brad.ac.uk/

[127] S. You, U. Neumann, and R. Azuma, "Hybrid inertial and vision tracking for augmented reality registration," in *Proceedings IEEE Virtual Reality*, Houston, TX, USA, 13-17 March 1999: IEEE, pp. 260-267.

[128] H. Kato and M. Billinghurst, "Marker tracking and hmd calibration for a video-based augmented reality conferencing system," in *Proceedings 2nd IEEE and ACM International Workshop on Augmented Reality (IWAR'99)*, San Francisco, CA, USA, 20 - 21 October 1999: IEEE, pp. 85-94.

[129] H. Park and J.-I. Park, "Invisible marker tracking for AR," in *Proceedings of the 3rd IEEE/ACM International Symposium on Mixed and Augmented Reality*, Arlington, VA, USA, 02 - 05 November 2004: IEEE Computer Society, pp. 272-273.

[130] I. E. Sutherland, "The ultimate display," *Multimedia: From Wagner to virtual reality,* vol. 2, pp. 506–508, 1965.

[131] F. Zhou, H. B.-L. Duh, and M. Billinghurst, "Trends in augmented reality tracking, interaction and display: A review of ten years of ISMAR," in *Proceedings of the 7th IEEE/ACM International Symposium on Mixed and Augmented Reality*, Cambridge, UK, 15-18 September 2008: IEEE Computer Society, pp. 193-202.

[132] A. O. Alkhamisi and M. M. Monowar, "Rise of augmented reality: current and future application areas," *International journal of internet and distributed systems,* vol. 2013, no. 1, pp. 25-34, 2013.

[133] J. Carmigniani, B. Furht, M. Anisetti, P. Ceravolo, E. Damiani, and M. Ivkovic, "Augmented reality technologies, systems and applications," *Multimedia Tools and Applications,* vol. 51, no. 1, pp. 341-377, 2011.

[134] S.-H. Hung, S.-W. Hsiao, Y.-C. Teng, and R. Chien, "Real-time and intelligent private data protection for the Android platform," *Pervasive and Mobile Computing,* vol. 24, pp. 231-242, 2015.

[135] T. Ghose, V. Namboodiri, and R. Pendse, "Thin is green: Leveraging the thin-client paradigm for sustainable mobile computing," *Computers & Electrical Engineering,* vol. 45, pp. 155-168, 2015.

[136] E. Mitchell, D. Monaghan, and N. E. O'Connor, "Classification of sporting activities using smartphone accelerometers," *Sensors,* vol. 13, no. 4, pp. 5317-5337, 2013.

[137] J. Ashburner, S. Vickerstaff, J. Beetge, and J. Copley, "Remote versus face-to-face delivery of early intervention programs for children with autism spectrum disorders: Perceptions of rural families and service providers," *Research in Autism Spectrum Disorders,* vol. 23, pp. 1-14, 2016.

[138] J. Kosmicki, V. Sochat, M. Duda, and D. Wall, "Searching for a minimal set of behaviors for autism detection through feature selection-based machine learning," *Translational psychiatry,* vol. 5, no. 2, p. e514, 2015.

[139] D. Wall, J. Kosmicki, T. Deluca, E. Harstad, and V. Fusaro, "Use of machine learning to shorten observation-based screening and diagnosis of autism," *Translational psychiatry,* vol. 2, no. 4, p. e100, 2012.

[140] P. Perego, S. Forti, A. Crippa, A. Valli, and G. Reni, "Reach and throw movement analysis with support vector machines in early diagnosis of autism," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2009)*, Hilton Minneapolis, Minnesota, September 2-6 2009: IEEE, pp. 2555-2558.

[141] A. Pratap and C. Kanimozhiselvi, "Predictive assessment of autism using unsupervised machine learning models," *International Journal of Advanced Intelligence Paradigms,* vol. 6, no. 2, pp. 113-121, 2014.

[142] W. Liu, L. Yi, Z. Yu, X. Zou, B. Raj, and M. Li, "Efficient autism spectrum disorder prediction with eye movement: A machine learning framework," in *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, Xian, China, September 21-24 2015: IEEE, pp. 649-655.

[143] Y. Zhou, F. Yu, and T. Duong, "Multiparametric MRI characterization and prediction in autism spectrum disorder using graph theory and machine learning," *PloS one,* vol. 9, no. 6, p. e90405, 2014.

[144] C. Ecker *et al.*, "Investigating the predictive value of whole-brain structural MR scans in autism: a pattern classification approach," *Neuroimage,* vol. 49, no. 1, pp. 44-56, 2010.

[145] W. Bosl, A. Tierney, H. Tager-Flusberg, and C. Nelson, "EEG complexity as a biomarker for autism spectrum disorder risk," *BMC medicine,* vol. 9, no. 1, pp. 1-18, 2011.

[146] J. Hashemi *et al.*, "A computer vision approach for the assessment of autism-related behavioral markers," in *Development and Learning and Epigenetic Robotics (ICDL), 2012 IEEE International Conference on*, 2012: IEEE, pp. 1-7.

[147] W. Jamal, S. Das, I.-A. Oprescu, K. Maharatna, F. Apicella, and F. Sicca, "Classification of autism spectrum disorder using supervised learning of brain connectivity measures extracted from synchrostates," *Journal of neural engineering,* vol. 11, no. 4, p. 046019, 2014.

[148] W. Liu, M. Li, and L. Yi, "Identifying children with autism spectrum disorder based on their face processing abnormality: A machine learning framework," *Autism Research,* vol. 9, no. 8, pp. 888-898, 2016.

[149] D. Bone, S. Bishop, M. P. Black, M. S. Goodwin, C. Lord, and S. S. Narayanan, "Use of machine learning to improve autism screening and diagnostic

instruments: effectiveness, efficiency, and multi-instrument fusion," *Journal of Child Psychology and Psychiatry,* vol. 57, no. 8, pp. 927-937, 2016.

[150] H. Behnam, A. Sheikhani, M. R. Mohammadi, M. Noroozian, and P. Golabi, "Analyses of EEG background activity in Autism disorders with fast Fourier transform and short time Fourier measure," in *International Conference on Intelligent and Advanced Systems*, Kuala Lumpur, Malaysia, November 25-28 2007: IEEE, pp. 1240-1244.

[151] S. Ghiassian, R. Greiner, P. Jin, and M. Brown, "Learning to Classify Psychiatric Disorders based on fMR Images: Autism vs Healthy and ADHD vs Healthy," in *Proceedings of 3rd NIPS Workshop on Machine Learning and Interpretation in NeuroImaging*, Nevada US, December 9-10 2013.

[152] J. R. Sato *et al.*, "Inter-regional cortical thickness correlations are associated with autistic symptoms: a machine-learning approach," *Journal of psychiatric research,* vol. 47, no. 4, pp. 453-459, 2013.

[153] S. Wang *et al.*, "Atypical Visual Saliency in Autism Spectrum Disorder Quantified through Model-Based Eye Tracking," *Neuron,* vol. 88, no. 3, pp. 604-616, 2015.

[154] X. Hua *et al.*, "Brain growth rate abnormalities visualized in adolescents with autism," *Human brain mapping,* vol. 34, no. 2, pp. 425-436, 2013.

[155] C. Ecker *et al.*, "Describing the brain in autism in five dimensions—magnetic resonance imaging-assisted diagnosis of autism spectrum disorder using a multiparameter classification approach," *The Journal of Neuroscience,* vol. 30, no. 32, pp. 10612-10623, 2010.

[156] M. Duda, R. Ma, N. Haber, and D. Wall, "Use of machine learning for behavioral distinction of autism and ADHD," *Translational psychiatry,* vol. 6, no. 2, p. e732, 2016.

[157] R. Guillén, C. Jensen, and S. Edelson, "A machine learning approach for identifying subtypes of autism," in *Proceedings of the 1st ACM International Health Informatics Symposium*, Virginia, USA, November 11 - 12 2010: ACM, pp. 620-628.

[158] D. Bone, M. S. Goodwin, M. P. Black, C.-C. Lee, K. Audhkhasi, and S. Narayanan, "Applying machine learning to facilitate autism diagnostics: Pitfalls

and promises," *Journal of autism and developmental disorders,* vol. 45, no. 5, pp. 1121-1136, 2015.

[159] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *Biomedical Engineering, IEEE Transactions on,* vol. 55, no. 8, pp. 1956-1965, 2008.

[160] M. Wedyan and A. Al-Jumaily, "Upper limb motor coordination based early diagnosis in high risk subjects for Autism," in *Computational Intelligence (SSCI), 2016 IEEE Symposium Series on*, 2016: IEEE, pp. 1-8.

[161] M. Wedyan and A. Al-Jumaily, "Early diagnosis autism based on upper limb motor coordination in high risk subjects for autism," in *Robotics and Intelligent Sensors (IRIS), 2016 IEEE International Symposium on*, 2016: IEEE, pp. 13-18.

[162] M. Wedyan and A. Al-Jumaily, "An investigation of upper limb motor task based discriminate for high risk autism," in *Intelligent Systems and Knowledge Engineering (ISKE), 2017 12th International Conference on*, 2017: IEEE, pp. 1-6.

[163] H. Abbas, F. Garberson, E. Glover, and D. P. Wall, "Machine learning approach for early detection of autism by combining questionnaire and home video screening," *Journal of the American Medical Informatics Association,* vol. 25, no. 8, pp. 1000-1007, 2018.

[164] G. Esposito, P. Venuti, F. Apicella, and F. Muratori, "Analysis of unsupported gait in toddlers with autism," *Brain and Development,* vol. 33, no. 5, pp. 367-373, 2011.

[165] J. Bo, C.-M. Lee, A. Colbert, and B. Shen, "Do children with autism spectrum disorders have motor learning difficulties?," *Research in Autism Spectrum Disorders,* vol. 23, pp. 50-62, 2016.

[166] R. Downey and M. J. K. Rapport, "Motor activity in children with autism: a review of current literature," *Pediatric Physical Therapy,* vol. 24, no. 1, pp. 2-20, 2012.

[167] M. Shetreat-Klein, S. Shinnar, and I. Rapin, "Abnormalities of joint mobility and gait in children with autism spectrum disorders," *Brain and Development,* vol. 36, no. 2, pp. 91-96, 2014.

[168] G. Dawson and R. Watling, "Interventions to facilitate auditory, visual, and motor integration in autism: A review of the evidence," *Journal of autism and developmental disorders,* vol. 30, no. 5, pp. 415-421, 2000.

[169] G. T. Baranek, "Efficacy of sensory and motor interventions for children with autism," *Journal of autism and developmental disorders,* vol. 32, no. 5, pp. 397-422, 2002.

[170] P. Turaga, R. Chellappa, V. S. Subrahmanian, and O. Udrea, "Machine recognition of human activities: A survey," *Circuits and Systems for Video Technology, IEEE Transactions on,* vol. 18, no. 11, pp. 1473-1488, 2008.

[171] S. Vishwakarma and A. Agrawal, "A survey on activity recognition and behavior understanding in video surveillance," *The Visual Computer,* vol. 29, no. 10, pp. 983-1009, 2013.

[172] M. Calhoun, M. Longworth, and V. L. Chester, "Gait patterns in children with autism," *Clinical Biomechanics,* vol. 26, no. 2, pp. 200-206, 2011.

[173] A. Poole and L. J. Ball, "Eye tracking in HCI and usability research," *Encyclopedia of human computer interaction,* vol. 1, pp. 211-219, 2006.

[174] D. C. Richardson and M. J. Spivey, "Eye tracking: Characteristics and methods," *Encyclopedia of biomaterials and biomedical engineering,* vol. 3, pp. 1028-1042, 2004.

[175] K. M. Dalton *et al.*, "Gaze fixation and the neural circuitry of face processing in autism," *Nature neuroscience,* vol. 8, no. 4, pp. 519-526, 2005.

[176] K. A. Pelphrey, N. J. Sasson, J. S. Reznick, G. Paul, B. D. Goldman, and J. Piven, "Visual scanning of faces in autism," *Journal of autism and developmental disorders,* vol. 32, no. 4, pp. 249-261, 2002.

[177] Y. Bar-Haim, C. Shulman, D. Lamy, and A. Reuveni, "Attention to eyes and mouth in high-functioning children with autism," *Journal of autism and developmental disorders,* vol. 36, no. 1, pp. 131-137, 2006.

[178] J. N. van der Geest, C. Kemner, G. Camfferman, M. Verbaten, and H. van Engeland, "Looking at images with human figures: comparison between autistic and normal children," *Journal of autism and developmental disorders,* vol. 32, no. 2, pp. 69-75, 2002.

[179] C. Chevallier *et al.*, "Measuring social attention and motivation in autism spectrum disorder using eye-tracking: Stimulus type matters," *Autism Research,* vol. 8, no. 5, pp. 620-628, 2015.

[180] P. Brambilla, A. Hardan, S. U. di Nemi, J. Perez, J. C. Soares, and F. Barale, "Brain anatomy and development in autism: review of structural MRI studies," *Brain research bulletin,* vol. 61, no. 6, pp. 557-569, 2003.

[181] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, "Review of brain MRI image segmentation methods," *Artificial Intelligence Review,* vol. 33, no. 3, pp. 261-274, 2010.

[182] B. S. Khundrakpam, J. D. Lewis, P. Kostopoulos, F. Carbonell, and A. C. Evans, "Cortical thickness abnormalities in autism spectrum disorders through late childhood, adolescence, and adulthood: a large-scale MRI study," *Cerebral Cortex,* vol. 27, no. 3, pp. 1721-1731, 2017.

[183] J. Piven, S. Arndt, J. Bailey, and S. Havercamp, "An MRI study of brain size in autism," *The American journal of psychiatry,* vol. 152, no. 8, p. 1145, 1995.

[184] D. P. Subha, P. K. Joseph, R. Acharya, and C. M. Lim, "EEG signal analysis: a survey," *Journal of medical systems,* vol. 34, no. 2, pp. 195-212, 2010.

[185] C. Rambabu and B. R. Murthy, "EEG signal with feature extraction using SVM and ICA classifiers," *International Journal of Computer Applications,* vol. 85, no. 3, pp. 1-7, 2014.

[186] M. G. Chez, M. Chang, V. Krasne, C. Coughlan, M. Kominsky, and A. Schwartz, "Frequency of epileptiform EEG abnormalities in a sequential screening of autistic patients with no known clinical epilepsy from 1996 to 2005," *Epilepsy & Behavior,* vol. 8, no. 1, pp. 267-271, 2006.

[187] A. Al-Jumaily and R. A. Olivares, "Electromyogram (EMG) driven system based virtual reality for prosthetic and rehabilitation devices," in *Proceedings of the 11th International Conference on Information Integration and Web-based Applications & Services*, Kuala Lumpur, Malaysia, 14-16 December 2009, pp. 582-586.

[188] E. McColl *et al.*, *Design and use of questionnaires: a review of best practice applicable to surveys of health service staff and patients*. Core Research, 2001, p. 256.

[189] S. McGrew, B. A. Malow, L. Henderson, L. Wang, Y. Song, and W. L. Stone, "Developmental and behavioral questionnaire for autism spectrum disorders," *Pediatric Neurology,* vol. 37, no. 2, pp. 108-116, 2007.

[190] N. Mori, K. Suzuki, K. Tsuchiya, C. Shimmura, H. Sakurai, and K. Tokutani, "Method, system and device for assisting diagnosis of autism," ed: Google Patents, 2017.

[191] G. Kumar and P. K. Bhatia, "A detailed review of feature extraction in image processing systems," in *2014 Fourth international conference on advanced computing & communication technologies*, Rohtak, India, February 08 - 09 2014, vol. 1: IEEE, pp. 5-12.

[192] R. N. Khushaba, A. Al-Ani, and A. Al-Jumaily, "Feature subset selection using differential evolution and a statistical repair mechanism," *Expert Systems with Applications,* vol. 38, no. 9, pp. 11515-11526, 2011.

[193] R. N. Khushaba, A. AlSukker, A. Al-Ani, A. Al-Jumaily, and A. Y. Zomaya, "A novel swarm based feature selection algorithm in multifunction myoelectric control," *Journal of Intelligent & Fuzzy Systems,* vol. 20, no. 4, 5, pp. 175-185, 2009.

[194] Y. M. Aung and A. Al-Jumaily, "Rehabilitation exercise with real-time muscle simulation based EMG and AR," in *2011 11th International Conference on Hybrid Intelligent Systems (HIS)*, Malacca, Malaysia, December 5-8 2011: IEEE, pp. 641-646.

[195] A. Hunter, "Feature selection using probabilistic neural networks," *Neural Computing & Applications,* vol. 9, no. 2, pp. 124-132, 2000.

[196] M. Mirmehdi, P. L. Palmer, and J. Kittler, "Genetic optimisation of the image feature extraction process," *Pattern Recognition Letters,* vol. 18, no. 4, pp. 355-365, 1997.

[197] Y. Chen, D. Miao, R. Wang, and K. Wu, "A rough set approach to feature selection based on power set tree," *Knowledge-Based Systems,* vol. 24, no. 2, pp. 275-281, 2011.

[198] S. Wang, D. Li, X. Song, Y. Wei, and H. Li, "A feature selection method based on improved fisher's discriminant ratio for text sentiment classification," *Expert Systems with Applications,* vol. 38, no. 7, pp. 8696-8702, 2011.

[199] A. R. Webb, *Statistical pattern recognition*, Second Edition ed. England: John Wiley & Sons, 2003.

[200] J. Ren, Z. Qiu, W. Fan, H. Cheng, and S. Y. Philip, "Forward semi-supervised feature selection," in *Advances in Knowledge Discovery and Data Mining*, Osaka, Japan, May 20-23 2008: Springer, pp. 970-976.

[201] S. Balakrishnama and A. Ganapathiraju, "Linear discriminant analysis-a brief tutorial," *Institute for Signal and information Processing,* vol. 18, pp. 1–8, 1998.

[202] O. Déniz, G. Bueno, J. Salido, and F. De la Torre, "Face recognition using histograms of oriented gradients," *Pattern Recognition Letters,* vol. 32, no. 12, pp. 1598-1603, 2011.

[203] Y.-X. Zhang and Y.-H. Zhao, "A comparison of BBN, ADTree and MLP in separating quasars from large survey catalogues," *Chinese Journal of Astronomy and Astrophysics,* vol. 7, no. 2, p. 289, 2007.

[204] N. Landwehr, M. Hall, and E. Frank, "Logistic model trees," *Machine Learning,* vol. 59, no. 1-2, pp. 161-205, 2005.

[205] C. J. Burges, "A tutorial on support vector machines for pattern recognition," *Data mining and knowledge discovery,* vol. 2, no. 2, pp. 121-167, 1998.

[206] W. S. Noble, "What is a support vector machine?," *Nature biotechnology,* vol. 24, no. 12, pp. 1565-1567, 2006.

[207] J. W. Riley, C. Alfons, E. Fredäng, and P. Lind, "Nearest Neighbor Classifiers," ed, 2009.

[208] R. Kohavi, "Scaling Up the Accuracy of Naive-Bayes Classifiers: A Decision-Tree Hybrid," in *KDD*, Portland, Oregon, August 2–4 1996, vol. 96: Citeseer, pp. 202-207.

[209] S. V. Sabnani, "Computer security: A machine learning approach," in "2008," Royal Holloway, University of London, London, 2008. [Online]. Available: https://core.ac.uk/download/pdf/21720707.pdf

[210] E. C. Alexopoulos, "Introduction to multivariate regression analysis," *Hippokratia,* vol. 14, no. Suppl 1, p. 23, 2010.

[211] E. Pulkstenis and T. J. Robinson, "Goodness-of-fit tests for ordinal response regression models," *Statistics in medicine,* vol. 23, no. 6, pp. 999-1014, 2004.

[212] X. Zhou, K.-Y. Liu, and S. T. Wong, "Cancer classification and prediction using logistic regression with Bayesian gene selection," *Journal of Biomedical Informatics,* vol. 37, no. 4, pp. 249-259, 2004.

[213] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology (TIST),* vol. 2, no. 3, p. 27, 2011.

[214] A. McCallum and K. Nigam, "A comparison of event models for naive bayes text classification," in *AAAI-98 workshop on learning for text categorization*, Madison, Wisconsin, July 26-27 1998, vol. 752: Citeseer, pp. 41-48.

[215] G. Biau, "Analysis of a random forests model," *The Journal of Machine Learning Research,* vol. 13, no. 1, pp. 1063-1095, 2012.

[216] S. Chen, C. F. Cowan, and P. M. Grant, "Orthogonal least squares learning algorithm for radial basis function networks," *Neural Networks, IEEE Transactions on,* vol. 2, no. 2, pp. 302-309, 1991.

[217] Microsoft, "Microsoft Kinect Joint Type," ed, 2017.

[218] K.-H. Li, S.-J. Lou, H.-Y. Tsai, and R.-C. Shih, "The Effects of Applying Game-Based Learning to Webcam Motion Sensor Games for Autistic Students' Sensory Integration Training," *Turkish Online Journal of Educational Technology-TOJET,* vol. 11, no. 4, pp. 451-459, 2012.

[219] F. Taffoni, V. Focaroli, F. Keller, and J. Iverson, "A technological approach to studying motor planning ability in children at high risk for ASD," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, IL, USA, 26-30 August 2014: IEEE, pp. 3638-3641.

[220] Microsoft. "Kinect for Windows." https://developer.microsoft.com/en-us/windows/kinect/hardware (accessed.

[221] S. Jackson, *The Art of Neural Networks Using C Sharp*. North Charleston, SC, United States: CreateSpace Independent Publishing Platform, 2016.

[222] A. G. D. Corrêa and R. de Deus Lopes, "A Criatividade através da expressão musical: uma interface gestual para composição musical interativa," *RENOTE,* vol. 2, no. 2, pp. 1-10, 2004.

[223] V. Geroimenko, "Augmented reality technology and art: The analysis and visualization of evolving conceptual models," in *2012 16th International*

Conference on Information Visualisation, Washington, DC, USA, 11 - 13 July 2012: IEEE, pp. 445-453.

[224] V. Focaroli, F. Taffoni, S. M. Parsons, F. Keller, and J. M. Iverson, "Performance of motor sequences in children at heightened vs. low risk for ASD: A longitudinal study from 18 to 36 months of age," *Frontiers in psychology,* vol. 7, pp. 1-9, 2016.

[225] J. P. Lima, F. Simões, L. Figueiredo, and J. Kelner, "Model based markerless 3D tracking applied to augmented reality," *Journal on 3D Interactive Systems,* vol. 1, pp. 2–15, 2010.

[226] H. Geissinger, "Educational software: Criteria for evaluation," in *Australian Society for Computers in Learning in Tertiary Education (ASCILITE)*, Perth, Western Australia, Australia, 7 -10 December 1997, pp. 219–223.

[227] R. Satsangi and B. Miller, "The case for adopting virtual manipulatives in mathematics education for students with disabilities," *Preventing School Failure: Alternative Education for Children and Youth,* vol. 61, no. 4, pp. 303-310, 2017.

[228] A. Zaidan, B. Zaidan, M. Hussain, A. Haiqi, M. M. Kiah, and M. Abdulnabi, "Multi-criteria analysis for OS-EMR software selection problem: A comparative study," *Decision support systems,* vol. 78, pp. 15-27, 2015.

[229] B. Galna, G. Barry, D. Jackson, D. Mhiripiri, P. Olivier, and L. Rochester, "Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease," *Gait & posture,* vol. 39, no. 4, pp. 1062-1068, 2014.

[230] K. Otte *et al.*, "Accuracy and reliability of the kinect version 2 for clinical measurement of motor function," *PloS one,* vol. 11, no. 11, p. e0166532, 2016.

[231] P. Xanthopoulos, P. M. Pardalos, and T. B. Trafalis, "Linear discriminant analysis," in *Robust Data Mining*. New York, NY: Springer, 2013, pp. 27-33.

[232] W. Dwinnell and D. Sevis, "LDA: Linear Discriminant Analysis," vol. 29673, ed: Matlab Central File Exchange, 2010.

[233] C. Pettersson and E. Schmidt, "Challenges With Session to Session Managementin Brain Computer Interfaces: A Comparison of Classification Methods for Motor Imagery Induced EEG Patterns," ed, 2014, pp. 1-39.

[234] X. Liu and H. Fu, "PSO-based support vector machine with cuckoo search technique for clinical disease diagnoses," *The Scientific World Journal,* vol. 6, pp. 1–7, 2014.

[235] T. Fletcher, "Support vector machines explained," ed, 2009.

[236] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: a new learning scheme of feedforward neural networks," *Neural networks,* vol. 2, no. 3, pp. 985-990, 2004.

[237] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: theory and applications," *Neurocomputing,* vol. 70, no. 1, pp. 489-501, 2006.

[238] Q.-Y. Zhu, A. K. Qin, P. N. Suganthan, and G.-B. Huang, "Evolutionary extreme learning machine," *Pattern recognition,* vol. 38, no. 10, pp. 1759-1763, 2005.

[239] K. Anam and A. Al-Jumaily, "Evaluation of extreme learning machine for classification of individual and combined finger movements using electromyography on amputees and non-amputees," *Neural Networks,* vol. 85, pp. 51-68, 2017.

[240] K. Anam and A. Al-Jumaily, "A novel extreme learning machine for dimensionality reduction on finger movement classification using sEMG," in *2015 7th International IEEE/EMBS Conference on Neural Engineering (NER)*, Montpellier, France, April 22-24 2015: IEEE, pp. 824-827.

[241] J. Kim, J. Kim, G.-J. Jang, and M. Lee, "Fast learning method for convolutional neural networks using extreme learning machine and its application to lane detection," *Neural Networks,* vol. 87, pp. 109-121, 2017.

[242] Z.-H. You, Y.-K. Lei, L. Zhu, J. Xia, and B. Wang, "Prediction of protein-protein interactions from amino acid sequences with ensemble extreme learning machines and principal component analysis," *BMC bioinformatics,* vol. 14, no. 8, pp. S10–21, 2013.

[243] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in *The 1995 International Joint Conference on AI IJCAI*, Montreal, Canada, 20-25 August 1995, vol. 14, no. 2, pp. 1137-1145.

[244] S. Datta, *Machine-learning with OpenCV*, 1st Edition ed. (Learning OpenCV 3 Application Development). Packt Publishing Ltd, 2016, pp. 1-310.

[245] W. Zhu, N. Zeng, and N. Wang, "Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS® implementations," in *NESUG proceedings: health care and life sciences*, Baltimore, Maryland, 14-17 November 2010, pp. 1-9.

[246] F. Taffoni, V. Focaroli, D. Formica, E. Gugliemelli, F. Keller, and J. M. Iverson, "Sensor-based technology in the study of motor skills in infants at risk for ASD,"

in *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2012: IEEE, pp. 1879-1883.

[247] V. Focaroli, F. Taffoni, S. M. Parsons, F. Keller, and J. M. Iverson, "Performance of motor sequences in children at heightened vs. low risk for ASD: A longitudinal study from 18 to 36 months of age," *Frontiers in psychology,* vol. 7, 2016.

[248] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature,* vol. 521, no. 7553, pp. 436-444, 2015.

[249] L. Deng and D. Yu, "Deep learning: methods and applications," *Foundations and Trends® in Signal Processing,* vol. 7, no. 3–4, pp. 197-387, 2014.

[250] C. C. Charalambous and A. A. Bharath, "A data augmentation methodology for training machine/deep learning gait recognition algorithms," in *2016 British Machine Vision conference BMVC 2016*, York, UK, September 19-22 2016, pp. 110.1-110.12.

[251] A. Masood and A. Al-Jumaily, "Semi-advised learning model for skin cancer diagnosis based on histopathalogical images," in *Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando, FL, USA, 16–20 August 2016: IEEE, pp. 631-634.

[252] D.-C. Li and I.-H. Wen, "A genetic algorithm-based virtual sample generation technique to improve small data set learning," *Neurocomputing,* vol. 143, pp. 222-230, 2014.

[253] K. A. Strauss, E. G. Puffenberger, and D. H. Morton, *Maple syrup urine disease* (GeneReviews®[Internet]). University of Washington, Seattle, 2013.

[254] Q. Fu *et al.*, "Radiographic features of hand osteoarthritis in adult Kashin-Beck Disease (KBD): the Yongshou KBD study," *Osteoarthritis and cartilage,* vol. 23, no. 6, pp. 868-873, 2015.

[255] E. S. o. Radiology, "Medical imaging in personalised medicine: a white paper of the research committee of the European Society of Radiology (ESR)," *Insights into imaging,* vol. 6, no. 2, pp. 141-155, 2015.

[256] A. Colubri, T. Silver, T. Fradet, K. Retzepi, B. Fry, and P. Sabeti, "Transforming clinical data into actionable prognosis models: machine-learning framework and field-deployable app to predict outcome of Ebola patients," *PLoS neglected tropical diseases,* vol. 10, no. 3, pp. 1-17, 2016.

[257] J. Vymetal *et al.*, "Emergency situations in rheumatology with a focus on systemic autoimmune diseases," *Biomedical Papers of the Medical Faculty of Palacky University in Olomouc,* vol. 160, no. 1, pp. 20–29, 2016.

[258] S. T. Ildstad and C. H. Evans Jr, *Small clinical trials: issues and challenges*. Washington, DC, USA: National Academies Press, 2001.

[259] G. Orru, W. Pettersson-Yeo, A. F. Marquand, G. Sartori, and A. Mechelli, "Using support vector machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review," *Neuroscience & Biobehavioral Reviews,* vol. 36, no. 4, pp. 1140-1152, 2012.

[260] D.-C. Li, C.-S. Wu, T.-I. Tsai, and Y.-S. Lina, "Using mega-trend-diffusion and artificial samples in small data set learning for early flexible manufacturing system scheduling knowledge," *Computers & Operations Research,* vol. 34, no. 4, pp. 966-982, 2007.

[261] C. Huang and C. Moraga, "A diffusion-neural-network for learning from small samples," *International Journal of Approximate Reasoning,* vol. 35, no. 2, pp. 137-161, 2004.

[262] L. Khot, S. Panigrahi, and S. Woznica, "Neural-network-based classification of meat: evaluation of techniques to overcome small dataset problems," *Biological Engineering Transactions,* vol. 1, no. 2, pp. 127-143, 2008.

[263] D.-C. Li, C.-C. Chen, C.-J. Chang, and W.-K. Lin, "A tree-based-trend-diffusion prediction procedure for small sample sets in the early stages of manufacturing systems," *Expert Systems with Applications,* vol. 39, no. 1, pp. 1575-1581, 2012.

[264] L. R. Khot *et al.*, "Evaluation of technique to overcome small dataset problems during neural-network based contamination classification of packaged beef using integrated olfactory sensor system," *LWT-Food Science and Technology,* vol. 45, no. 2, pp. 233-240, 2012.

[265] D.-C. Li, L.-S. Chen, and Y.-S. Lin, "Using functional virtual population as assistance to learn scheduling knowledge in dynamic manufacturing environments," *International Journal of Production Research,* vol. 41, no. 17, pp. 4011-4024, 2003.

[266] D.-C. Li and C.-W. Yeh, "A non-parametric learning algorithm for small manufacturing data sets," *Expert systems with applications,* vol. 34, no. 1, pp. 391-398, 2008.

[267] G.-Y. Chao *et al.*, "A new approach to prediction of radiotherapy of bladder cancer cells in small dataset analysis," *Expert Systems with Applications,* vol. 38, no. 7, pp. 7963-7969, 2011.

[268] D.-C. Li and Y.-S. Lin, "Using virtual sample generation to build up management knowledge in the early manufacturing stages," *European Journal of Operational Research,* vol. 175, no. 1, pp. 413-434, 2006.

[269] R. Johnson and D. Wichern, *The multivariate normal distribution*, 6th edition ed. (Applied Multivariate Statistical Analysis.). Englewood Cliffs, NJ: Prentice-Hall Inc, 1982, pp. 150-173.

[270] P. D. Scott and E. Wilkins, "Evaluating data mining procedures: techniques for generating artificial data sets," *Information and software technology,* vol. 41, no. 9, pp. 579-587, 1999.

[271] L. R. Khot, "Characterization and pattern recognition of selected sensors for food safety applications," PhD, Agricultural and Biosystems Engineering, North Dakota State University, Fargo, North Dakota, United States, 2009.

[272] D.-C. Li, C.-W. Liu, and W.-C. Chen, "A multi-model approach to determine early manufacturing parameters for small-data-set prediction," *International Journal of Production Research,* vol. 50, no. 23, pp. 6679-6690, 2012.

[273] P. Niyogi, F. Girosi, and T. Poggio, "Incorporating prior information in machine learning by creating virtual examples," *Proceedings of the IEEE,* vol. 86, no. 11, pp. 2196-2209, 1998.

[274] D.-C. Li, Y.-H. Fang, Y.-Y. Lai, and S. C. Hu, "Utilization of virtual samples to facilitate cancer identification for DNA microarray data in the early stages of an investigation," *Information Sciences,* vol. 179, no. 16, pp. 2740-2753, 2009.

[275] D. Dheeru and E. K. Taniskidou, "UCI machine learning repository: data set," ed, 2017.

[276] Y. Liu, Y. Zhou, X. Liu, F. Dong, C. Wang, and Z. Wang, "Wasserstein GAN-based small-sample augmentation for new-generation artificial intelligence: A case study of cancer-staging data in biology," *Engineering,* vol. 5, no. 1, pp. 156-163, 2019.

[277] C. Martin and C. Springate, "Synthetic Sample Generation Representing the English Population Using Spearman Rank Correlation and Chomsky Decomposition," *Value in Health,* vol. 21, p. S221, 2018.

[278] MathLab. "Normally Distributed Random Numbers." https://www.mathworks.com/help/stats/normrnd.html (accessed.

[279] J. Yang, X. Yu, Z.-Q. Xie, and J.-P. Zhang, "A novel virtual sample generation method based on Gaussian distribution," *Knowledge-Based Systems,* vol. 24, no. 6, pp. 740-748, 2011.

[280] UCI. "Machine Learning repository." University of California. https://archive.ics.uci.edu/ml/index.php (accessed 2 December 2017.

[281] M. Lichman. "UCI machine learning repository." University of California. https://archive.ics.uci.edu/ml/index.php (accessed.

[282] MathLab. "Train Stacked Autoencoders for Image Classification." https://www.mathworks.com/help/deeplearning/examples/train-stacked-autoencoders-for-image-classification.html (accessed 25 November 2018.

[283] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation," *The Scientific World Journal,* vol. 2014, 2014.

[284] N. Kalchbrenner, E. Grefenstette, and P. Blunsom, "A convolutional neural network for modelling sentences," *Proceedings of the Association for Computational Linguistics (ACL),* pp. 655-665, 2014. [Online]. Available: https://ui.adsabs.harvard.edu/abs/2014arXiv1404.2188K.

[285] D. Svozil, V. Kvasnicka, and J. Pospichal, "Introduction to multi-layer feed-forward neural networks," *Chemometrics and intelligent laboratory systems,* vol. 39, no. 1, pp. 43-62, 1997.