Emotion Recognition Techniques for Geriatric Users: A Snapshot

Abstract—**Several elderly people prefer their independence, however due to cognitive impairment or other age-related ailments they cannot necessarily be left on their own. In order to aid the elderly in living independently, we consider the use of emotion recognition as a relatively autonomous monitoring approach for geriatric people. An analysis and comparison among various emotion recognition studies has shown a that to the best of my knowledge, close to none of these studies have taken age related cognitive impairment into account, which comes with various issues, some pertaining to emotion production and perception. The aim of this paper is to provide an overview of current emotion recognition techniques and why they may not necessarily be suitable or feasible for geriatric people. This analysis serves as a foundation for a proposed conceptual framework toward an autonomous monitoring system for geriatric people which could minimize the need for explicit user input or interaction while still monitoring the geriatric person(s) well-being.**

Index Terms—**geriatric, elderly, emotion recognition, smart devices, facial recognition, gait recognition**

I. Introduction

In the past, studies have found that the elderly are more susceptible to mental health issues [1], [2]. They experience stressful encounters that are also endured by the younger generation, as well as stressors encountered later in life such as continuing loss in capabilities and a declining set of functional abilities. Additional stressors could even include socioeconomic status drops due to retirement. These experiences can lead inadvertently lead to psychological distress or deeper mental health issues for the elderly [1]. Aside from this, the elderly are also more vulnerable to abuse of various sorts such as psychological, verbal or physical abuse among others [1]; which could also result in anxiety or depression with cognitive impairment diseases such as Alzheimer's or Dementia face deterioration of mental functions as well as a likelihood of changing personality traits.

This makes it difficult or impossible for family members to be at ease letting their elders live alone, while some elders insist on staying on their own regardless, for a semblance of independence. Some elderly insist on staying on their own for a semblance of independence. On the other hand, there are some elderly persons that have no preference, but their families may be unable to due to loss of income or being faced with additional expenses that may not necessarily be covered under insurance [3].

This leads to caregiver burden as family members try to determine how to best care for or how to assist the person [4]. There is generally an increasing number of elderly persons living alone worldwide [5]. A possible solution to this is an enhanced monitoring system that allows the elderly to live alone with minimal to no caregiver burden or dependence. A potential approach could be the implementation of a more implicit and independent monitoring system that uses Emotion Recognition (ER) methods. With this paper we aim to put together an analysis of the most common emotion recognition techniques being used by researchers. The analysis focuses on common methods, as well as the feasibility and convenience of use for the study subjects, ambient settings, and whether the study uses a multimodal ER approach. Most importantly we look at the applicability of the respective methods with the geriatric generation as main study subjects.

This paper is structured as follows: Section II gives a brief overview on ER and why there is a need for more focus on the geriatric generation and ER practices. Section III shows the methodology for literature selection, followed by a literature review in Section IV. Section V focuses on the findings of the literature review, i.e. the gaps, challenges and limitations of past ER techniques. Our proposed conceptual framework, derived from our findings is detailed in Section VI and finally, conclusions and future work can be found in Section VII.

II. Related Work

Emotion recognition is the processing and perception or identification of human emotion. This is commonly done either by facial cues or by explicit verbal expression. While this is something most humans can easily do, there are ongoing studies to enable this to be automated as well. Some cases where humans tend to find difficulty perceiving or expressing emotions could be if they have Autism, Asperger's, or age induced cognitive deterioration. In the case where the use of or the ability of verbal expression is not hindered, geriatric patients are still known to report depressed emotions lesser than younger patients do, which also leads to increased anxiety [2].

These days there are various studies focusing on using on-body sensors or wearable devices such as smartwatches or smartphone sensors in ongoing attempts toward smarter emotion recognition [6]–[9]. However, these studies require an explicit form of user input, such as being in a set frame of reference for facial recognition or requiring an on-body sensor like an Electroencephalography (EEG), Electrocardiography (ECG) device. While younger users adapt to emerging technologies and devices at a swift pace, the elder generation tends to face challenges in this respect, experiences cognitive deterioration with age or ails with Alzheimer's or Dementia [10].

Some focus has been placed on determining the connection between explicit physiological signals and implicit internal feelings [11]. There are studies on emotion recognition using various kinds of sensors. The ability to infer emotions in facial expressions gets more difficult with age related cognitive impairment, and at a higher rate in the case of deterioration in cognitive function [12], leading to apprehension or even frustration and avoidance as a whole [10]. This is further emphasized when the user.

The study also found that recognition of positive emotions is less impaired with a severe decline in cognitive function as opposed to negative emotions. Test participants had a higher accuracy when inferring positive emotions like happiness (69.3%) in comparison to anger (50.8%) and sadness (45.8%). Ostos et al. [13] additionally observed that there is selective impairment in disgust and fear recognition with increasing cognitive impairment due to progressive damage to neural structures linked to emotion and facial recognition. Park et al. [14] carried out tests and found further evidence on Facial Emotion Recognition impairment in patients with frontotemporal dementia (FTD), Alzheimer's disease (AD), and those with mild cognitive impairment (MCI). To do this, the study examined the FER performance of patients with FTD, AD, and those with MCI against healthy controls (HCs). Their approach found that the recognition of negative emotions differentiated between participants with FTD and those with MCI, AD or HCs. The recognition of positive emotions showed no differentiation. They also stated that there is still a need for more enhanced emotion recognition tools.

There have also been studies on exploiting smart home technologies for activity recognition. One such study by Ding, Yasmin van, Dana, Qing, Mohan and Hang [15] specifically focused on the aging generation. However, the study focused on activity recognition only, and required a relative level of explicit user input and interaction. There were also cases of false triggers due to a lack of capabilities to handle exceptions caused by variations in the daily routines of the elderly.

Shu et al. [11] contend that while physiological data is a more definitive method for determining a person's emotional state, there is still a certain level of difficulty in inferring one's emotional state using a single physiological signal individually. They hypothesized that combinations of various physiological sensors could lead to enhancements in emotion recognition approaches. They carried out a comprehensive review on various current physiological signal-based emotion recognition approaches. The review evaluated EEG, ECG, HR, GSR, RSP, and EMG methods proposed by researchers for emotion recognition. Smoothing filters and additional noise extraction methods were also used to remove any interference or background noise such as respiration sinus arrhythmias (RSA) from RSP or eye blinks from EEGs. The review assessed emotion recognition frameworks as well as common setups for high quality physiological data acquisition. Also taken under assessment were the conditions under which study participants must remain in order for apt data collection, such as sitting motionless in front of a screen for visual emotion elicitation. The review also observed quite a few challenges faced by researchers using physiological signals for emotion recognition, starting off with emotion elicitation. They found that the process of emotion elicitation is commonly carried out in a lab-based setup, with the test subject sitting motionless in front of a screen with emotion triggering stimuli being played for them.

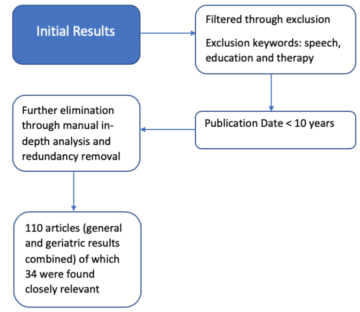

Fig. 1. Paper Selection Process Flow

As the aim of this study is to survey the literature and identify the current gaps in the field, here we conduct a review and present the most relevant work in this field. The next section presents the methodology followed for this review.

III. Methodology

A. Databases Searched

Relevant literature was found using peer-reviewed databases in the fields of health, computer science, information technology, affective computing and mental health. Databases used included PubMed, JMIR, ACM Digital Library, IEEE Explorer, Springer, Science Direct and Scopus.

B. Criteria

Search results were filtered through certain criteria to be selected for further analysis. Search terms included the main focal points such as elderly, geriatric, and emotion recognition. To further narrow down on relevant papers extra keywords were added such as cognitive impairment. Some keywords were added for search exclusion purposes, some being education and speech. This was done as a large amount of search results included education and speech evolution centered literature.

Two different searches were carried out, one for general emotion recognition studies and one focused on geriatrics. The main search was carried out with the following two search strings, with minor variations for further depth and relevance. After the initial search, papers were manually filtered to find the those most relevant to this review.

Initial search string:
emotion recognition AND !"education" AND !"speech".

Geriatric centered resulting search string:
emotion recognition AND "cognitive impairment" AND "elder*" OR "geriatric*" AND !"education" AND !"speech".

TABLE I
EMOTION RECOGNITION STUDIES BY DEVICE TYPE

Type	Author	Year	Multimodal	Physiological Input
On-body Device	Egger	2019	Y	Y
	Shu et al.	2018	Y	Y
	Benaissa et al.	2017	Y	Y
	Soroush et al.	2017	N	Y
	Thanh et al.	2017	Y	Y
	Jamil et al.	2015	N	Y
Smart Device	Lee et al.	2018	N	Y
	Chen & Shen	2017	Y	N
	Quiroz, Yong & Geangu	2017	Y	Y
	Ding et al.	2017	N	N
Wireless	Adib	2019	N	Y
	Barrett et al.	2019	N	N
	Rozanska et al.	2018	Y	N
	Zhao, Adib & Katabi	2016	N	N
	Kadir et al.	2014	N	Y
	Schneider et al.	2014	N	Y
	Wang et al.	2014	N	Y
	Wiechetek Ostos et al.	2011	N	N
	Michalak et al.	2009	Y	Y
	Hsu & Chien	2009	N	N

Results of both strings were further filtered to publication dates within the past 10 years to capture the state of the research. The most relevant papers were on emotion recognition techniques such as facial recognition, gait recognition, and physiological sensors.

C. Information Analysis

From the initial results pool, papers were manually filtered through by reading through the abstract and conclusion to find papers focusing on emotion recognition techniques, the conditions under which the studies carried out (lab-based or real-time setting), method of user data collection (contact versus non-contact) as well as potential applicability to geriatric users. Redundancy was avoided by removing repeat results. We then carried out an in-depth analysis of remaining papers by removing items that were not as relevant as initially assumed. We then looked into the contributions, practices, limitations and challenges of the remaining papers.

The next section provides a detailed look into current relevant emotion recognition studies and the methods and approaches they adopted. The literature is grouped based on similarities in methods used.

IV. REVIEW OF EMOTION RECOGNITION TECHNIQUES

Table 1 groups together information on studies based on the type of device. While under the same category, on-body devices refer to relatively obtrusive devices such as EEG headsets and

chest-mounted monitors; and smart devices refer to wearables that are much less obtrusive. Wireless devices come under non-contact.

Majority of the studies adopted non-contact means such as facial recognition, followed by on-body contact devices such as chest mounted heart rate monitors (Fig. 3a). Other studies focused on smart devices such as smart homes (non-contact) and smart watches (contact). Below is a further in-depth analysis of the selected papers.

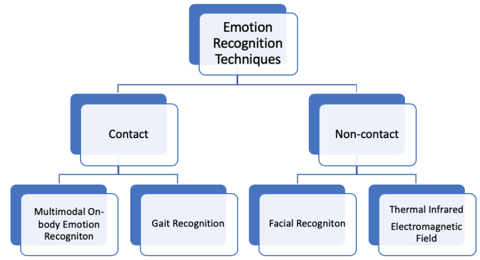

Fig. 2. Categorization of Emotion Recognition Techniques

Fig. 2 shows an overview of how the two main categories are further split up in this paper.

A. Contact Emotion Recogntion

1) Multimodal Emotion Recognition: Souroush et al. [16] focus more toward the use of various physiological methods for emotion recognition, such as online versus offline recognition, on-body measurements (EEG, ECG) as well as emotion stimulation approaches used alongside some of the reviewed studies. The review is an organized amalgamation of recent studies on emotion recognition with a greater focus on EEG based studies. It also reiterated the fact that there is no consensus on the nature of emotions. Additionally, environmental variations lead to physiological changes inevitably resulting in an effect on one's emotions. Along the physiological sensor route, Thanh et al. [17] detect emotions using musical therapy with three physiological sensors for a multimodal emotion recognition approach . They use music of various genres to trigger or alter different emotions alongside Galvanic Skin Response (GSR), Electromyography (EMG), and ECG to gather emotion data. The multimodal approach grouped the emotions into three categories: neutral, joy, and pleasure; with the highest accuracy being 93.175% for Pleasure classification. The study showed to have achieved an improved recognition rate using their multimodal approach in comparison to other current emotion recognition approaches. While the classification method demonstrated accuracy in emotion recognition, this method still requires on-body devices to collect data to process and infer emotions.

Benaissa et al. [18] state that heart beat rate and breathing are used in various studies for emotion recognition as they are strong indicators of emotions. While other emotion recognition approaches are not very efficient in elderly monitoring, this method is more applicable in this case. The paper notes that facial thermal imaging is an ongoing challenge for emotion recognition; their own proposed approach makes use of heartbeat rate, breathing and thermography together for a more efficient multimodal approach focusing on elderly emotion recognition. In their method, they propose positioning the sensor on the subject's chest for activity recognition. For emotion recognition the optimal sensor placement was on both sides of

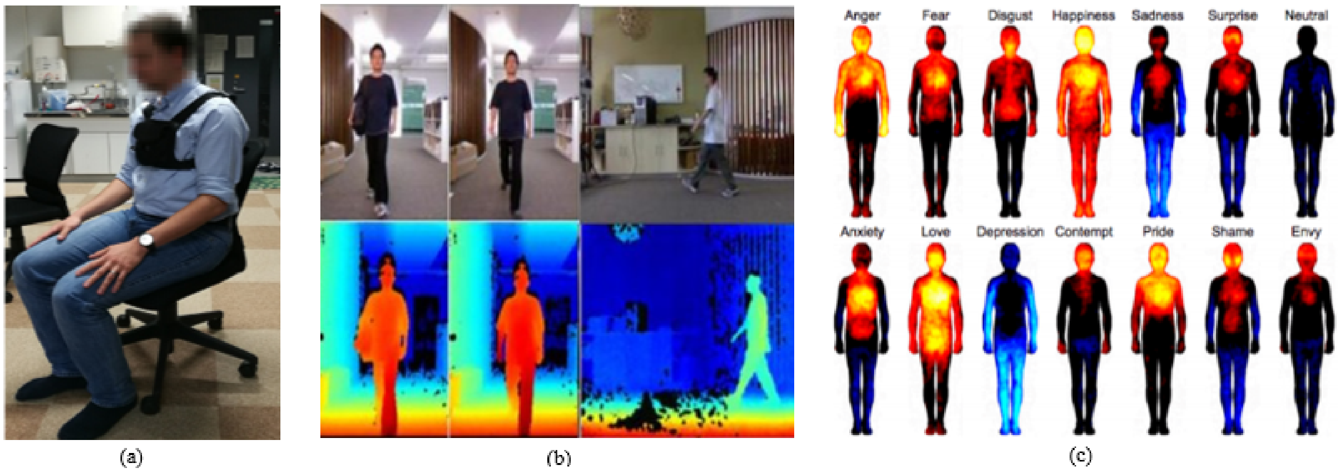

Fig. 3. (a) On-body chest mounted sensor [18] (b) In-house gait recognition [32] (c) Body Atlas of heat distribution with changing emotions [24]

the human chest to collect breathing data using the heartbeat rate. Alongside this, they propose using thermography for facial thermal imaging. Their proposal suggests using a combination of these sensors for enhanced emotion recognition. The method can be imagined to work as a comfortable wearable instead of an on-body chest strap on device.

Hsu and Chien [5] propose a system that uses various sensors for emotion recognition in attempting to aid the elderly live alone. They use inputs like hand gestures, facial expressions, and physiological signals in order to infer emotions, as well as ambient data such as lighting intensity, temperature levels, and humidity levels. The study focuses more on the algorithmic aspect of using the data collected from the aforementioned signals or sensors. While the proposed system could aid the elderly in living alone, it requires a large amount of explicit user interaction and input. The study hasn't taken into account the implications of age based cognitive decline and relies on facial expressions, which as mentioned earlier relies entirely on outward expression, which may be impaired or withheld more frequently in the elderly.

2) Gait Recognition: While there is a plethora of facial emotion recognition methods and studies, researchers have observed that recent studies in psychology have shown a relation in a person's emotions and the way they walk [19]. Lee et al. [19] carried out a study to unobtrusively collect data and propose an enhanced emotion recognition approach, outside of a potentially mood altering laboratory setup. The aim of the study was to infer participant emotions using smartwatch sensor data. To analyze the relation between a person's emotional state and their gait, they had participants walk with a smartwatch on their wrist as well as a heart rate monitor strapped to their chest. Participants were asked to watch audio-visual clips and listen to audio (happy/sad) stimuli to alter their emotions and corresponding gait. The study provides evidence that a person's emotions can be inferred using movement sensor data. However, they require further validation in order to definitively state that movement sensor data can in fact, be used for emotion recognition.

An earlier study by Jamil et al. [20] attempted to use gait analysis to detect emotions in Autistic children. Like Alzheimer's or Dementia patients not a lot of emotion recognition methods, particularly gait recognition in this case have been applied or tested on Autistic children. The study however required the children to wear bodysuits with markers on them, which was intolerable for some of the autistic children. The children erratically moved around, out of the assigned camera frame and removed the markers off their bodysuits. While Autistic children are not the focus of the study at hand, it relates in the target group (the elderly) possibly being non-verbal or unable to determine and express their own emotions. As mentioned earlier, Grunberg [3] stated that children and geriatric persons share characteristics in their lack of independent capabilities. Both age groups require similar care and a relatively similar level of dependence on caregiver. The elderly also have a tendency to be unpredictable with their movements and emotional responses to stimuli [4]. The study by Jamil, Khir, Ismail and Razak [20] added that there are earlier studies that have taken on gait recognition. However, none of them have focused on children with autism, to the best of their knowledge. Similarly, there do not appear to be any studies on using gait-based emotion recognition with the elderly geriatric persons as test participants so far.

B. Non-contact Emotion Recognition

Body language serves as an integral element of nonverbal communication which is normally perceived before expressions [21]. More and more studies are focusing on wireless methods for data collection, leading to emotion classification in an unobtrusive manner. One of the most common approaches in the literature discussed so far is facial recognition. There is, however, a growing interest toward using non-contact means of emotion recognition data, for example, thermal imaging or electromagnetic radio waves off the human body [22]. As mentioned earlier, a study by Fadel Adib [22] used wireless Radio Frequencies (RF) to detect human activity through walls as well as infer user emotions. Fig. 3b shows sample images of how non-contact gait patterns are tracked. Further discussed below are a few of the studies focusing on non-contact emotion recognition:

1) Facial Recognition: As a potential improvement, Rozanska et al. [23] propose an embedded system that implements various emotion recognition methods in an Internet of Things (IoT) device for remote emotion detection. Their proposed system consisted of a robot device with computer vision camera. When a person or multiple people approach the robot, it would be able to detect and infer their emotions. As the system is meant to be an IoT setup, it also uses sound, video, and speech-to-text analysis and recognition, including the choice of words and tone. They make use of body language and mimical expressions to infer emotions and found that some positive emotions like happiness are detectable at a longer distance. Negative emotions like sadness require a shorter distance to the device for accurate detection. On the other hand, there is anger, which is better inferred through body posture as opposed to facial mimicry features. While the system works, it requires between 14 to 20 seconds for emotion recognition and classification which is a relatively long processing time.

2) Thermal Infrared/Electromagnetic Field: Some researchers are focusing more on studying thermal infrared images for emotion recognition. An article by Jessica Leber [24] mapped heat distributions in the human body based on their emotions. It showed that anger is felt more in a person's head, while positive emotions like happiness or love are spread throughout the body [25]. Negative emotions like depression and sadness on the other hand show a deactivation of sensations in comparison to other less negative emotions. The article was based on an earlier study by Finnish researchers on the 'Body Atlas', which demonstrates how differently emotions are manifested in the body. Fig. 3c above shows the aforementioned 'Body Atlas'. The study proposes the use of the Bolztmann machine for emotion recognition using thermal infrared facial images. Their method outperformed other approaches using temperature statistic features or handcrafted features. [26] noted that the human electromagnetic field (EMF) changes with varying activities and health. Their study used EMF readings to distinguish left hemisphere stroke patients. Their study found that left hemisphere stroke patients have lower frequencies on the left side in comparison to the right side. A following study by them /citeb27 also showed that both left or right hemisphere stroke patients have significantly lower electromagnetic radiations (EMR) in comparison to non-stroke patients. Similarly, Murat et al. [28] collected electromagnetic radiations and aura analysis to determine physical and psychological fitness among Down syndrome and Non-Down Syndrome participants. Zhao et al. [29] exploit the positive aspects of audio-visual and physiological sensors based approaches and propose a new method to achieve viable outcomes in emotion recognition, without the limitations of on body or audio-visual sensors. To do this, they use RF signal reflections off the human body to infer their body movements and emotions. Their new algorithm extracts heartbeats from wireless signals that are then fed to a machine learning emotion classifier, leading to emotion recognition. The study also notes that while smartphones are also used for emotion classification; they require a prolonged time frame to personalize the analyses. The algorithm proposed on the other hand operate on minute-scale intervals. This study is seemingly the first to be exploiting RF signals from body reflections to infer user emotions as yet. It is one to follow closely as the objective is close to, if not almost the same as that of the approach being introduced in the study.

C. Discussion

While other studies tend to have pre-set classification models that may apply for younger subjects, they may be inefficient for elderly users. This is due to the fact that the elderly tend to be more unpredictable and aberrant in their behaviors [4], which could serve as anomalies or outliers for current trained classification models. It could be plausible that with age it also gets harder for a person to infer and express their own emotions. Hence, researchers need to further analyze physiological changes to study and classify emotions, while keeping into account the likelihood of artefacts that could obstruct data collection. Many of the studies discussed above have introduced new approaches, multimodal approaches or enhanced versions of previous approaches for emotion recognition. Having said that, there are still a few issues left lacking or untouched. One such issue is that of the aging generation not being highly tech friendly as opposed to the younger generation that can adapt much quicker.

1) Contact Emotion Recognition: While there are various emotion recognition studies at the moment, they come with certain limitations. A physiological sensor such as an ECG monitor can inadvertently alter a person's mood by being a hindrance to everyday activities and become a frustrating on body attachment. Lee et al. [19] also similarly stated that emotions are not necessarily a conscious function. Rather they are a reaction to surrounding stimuli or ambience. Laboratory based setup ups on large on-body sensors like chest strap on contraptions or EEG devices for example, can serve as obstructive devices inadvertently leading to mood unwanted alterations.

Further on there is the matter of data collection, Shu et al. [11] stated that data collected in lab based setups rely heavily on the stimuli provided to trigger or provoke specific emotions. Lee et al. [19] similarly stated that while emotions are shown in various ways such as voice, body language, gait or face, strict laboratory based setups may obstruct the validity of the collected data. Shu et al. [11] reiterated that there needs to be more work toward creating more natural, realistic ambience for data collection in order to garner accurate genuine emotions. The second issue found was that of subjective responses to external stimuli and general emotion production. Different people have different emotional responses to different scenarios and stimuli, due to which there is yet to be a fully tried and tested method that provides high quality physiological affect analysis data.

Additionally, there were different physiological responses with varying intensities of emotion stimulation [21]. This serves as an obstacle along the way of person independent, real-time applications of this physiological methods for emotion recognition. There is also the matter of small population sizes for test groups, resulting in small data sets. Hence, there is a need for larger scale studies for physiological sensor-based emotion recognition.

2) Non-contact Emotion Recognition: Another point raised is how the way people express anger, disgust, fear, happiness, sadness, and surprise significantly differs across cultures, situations, and even across people within a single situation. More so, a set classification for a scowl may not detect what a person is actually feeling, it is plausible that it may communicate something other than one's emotions.

Considering the fact that facial movements demonstrate a plethora of emotions, there is a dire need for more studies that focus on examining how facial movements actually vary alongside other social inputs that lead to a conclusive foundation on how humans perceive emotions [31].

In the case of voice or speech recognition, we must consider the likelihood of an elderly person possibly being non-verbal due to age related conditions such as a stroke for example.

While facial recognition is definitely a wireless means of gathering data to infer emotions, but it requires the person to be within a set frame for the camera. Aging persons especially those with cognitive impairment like Alzheimer's or Dementia are often unpredictable and atypical in their behaviors [4], which could in turn be another obstacle with facial recognition where the person has to be within a set frame for detection. This also entails explicit user interaction with the emotion recognition method or system. Aside from requiring explicit user input or interaction, facial recognition depends entirely on outward expression. Expressions contribute about 55% to the effect of the message being conveyed, with vocal tone contributing 38% and vocal cues contributing 7%. Taking these factors into account, they carried out experiments focusing on facial emotion recognition using images. The method showed to be working in improving the AAL experience for the elderly. However, the proposed method still requires further enhancement for more accuracy as well as to take video inputs into account as opposed to only images. Some researchers [23] on the other hand state that while facial recognition is of particular importance in non-verbal communication, it is a mistake to focus solely on the face for emotion recognition.

Shu et al. [11] stated that physical signals such as facial expressions or speech are not heavily reliable as it is fairly easy for people to control outward physical expressions. This

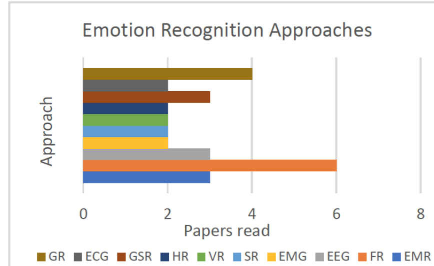

Fig. 4. Common Emotion Recognition Methods used by Researchers in the Recent Years

can be demonstrated by a person in a social gathering smiling while being in a negative emotional state.

However, the features being used in most of current emotion recognition studies are still focusing on facial thermal imaging [18], [31]. They adopt temperature statistical features extracted from facial regions of interest or those commonly used in the visible spectrum. So far there are no image features designed specifically for thermal infrared imaging [31].

Using the visual route another study demonstrated using gait recognition for human identification (Fig. 3b). They created an in-house gait database for gait recognition [32]. While their study does not focus on emotion recognition using gait, there could be potential applicability for gait recognition through non-contact means as well.

A majority of emotion recognition studies focus of facial emotion recognition with only a few focusing on the elderly [14], [15], [18], [33], particularly with Alzheimer's for the elderly generation. They raised attention to the fact that while smart homes are intended to aid the elderly in with their daily needs, the technologies involved are unfamiliar to the elderly generation, due to which they are often uncomfortable with the implementations. In order to bridge this gap, robots are proposed to act as the intermediary between the sensors/devices and the elderly. For this to be effective, the robot needs to be at the same level of communication and understanding as the user. In an attempt to improve this method of the AAL smart home experience, the study aimed at using facial emotion recognition. According to them, facial

Shu et al. [11] also contend that facial expressions are not the most reliable mode of emotion recognition. A phenomenon called 'facial mimicry' shows that when watching movie clips, or given a stimulus to alter emotions, expression of the same emotion will appear on the subjects face as well. While this shows empathy, it does not necessarily facilitate emotion recognition on persons in the absence of external stimuli. Similarly, outward expressions can be falsified easily or may simply not reflect what the person is actually feeling [11], [30].

Fig. 4 shows that facial recognition is still the most studied emotion recognition approach among the literature discussed so far. Other approaches as mentioned earlier, rely on audio-visual or physiological data collected through cameras, on-body sensors or wearable devices.

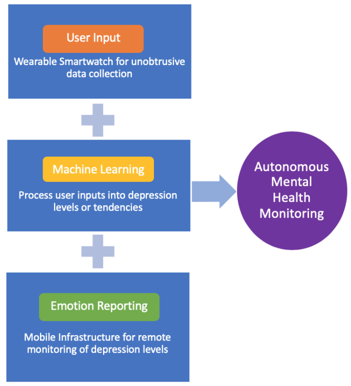

Fig. 5. Autonomous Mental Health Monitoring for the Elderly Framework

There is an evident gap in implicit emotion recognition, as well as emotion recognition approaches being implemented or tested with the elderly generation as the target subjects or test participants.

V. Conceptual Framework for ER in the Elderly

Based on the literature review, we narrowed down on wearable devices such as smartwatches being relatively least obtrusive among the other most common data collection methods. Physiological inputs like gait patterns, sleep patterns and heart rate are closely affected with shifting emotions. This combination of inputs and unobtrusive data collection can be paired with machine learning to classify and detect depression or depressive tendency for the user.

The conceptual framework (Fig. 5) shows the proposed stages leading up to an improved ER approach focusing on geriatric people.

A. User Input

As a major focus of this study is minimal user interaction, there needs to be a means of user data collection. From the review on recent emotion recognition studies, wearable devices have shown to be the least intrusive of all other common approaches such as on-body chest monitors or EEG headsets. In the case of facial recognition, the user needs to be within the camera's frame of focus and speech recognition requires explicit user interaction.

Based on this we have decided to use wearable smartwatches to collect the user's physiological data that is most commonly altered with shifting emotions (walking, sleep and heart rate). This combination of physiological factors appears to be ideal for accurate and more precise emotion classification as opposed to individual factors on their own.

B. Machine Learning

This component of the proposed framework essentially serves as the 'brains' of the monitoring system which will process and classify how depressed the user is or their depressive tendency.

The data collected from the smartwatch will be used to determine the ideal combination of factors for the highest accuracy of depression classification; e.g. gait + sleep, gait + heart rate, heart rate + sleep, gait + heart rate + sleep. Collected data will first be pre-processed and then be used to train the classification or regression model to classify or score the persons mental health level. Followed by testing the performance accuracy in the final validation stage.

C. Emotion Reporting

For reporting, a mobile app will be used to provide updates or notify caregivers of the user's mental health levels, depression or depressive tendency in this case. This maybe to caregiver staff, or family members.

The app will mainly focus on reporting the user's depression levels, however since the user's physiological data will is going to be stored as well, it is likely the app will include visuals of heart rate levels, sleep patterns as well as gait information. To avoid subconscious emotion alteration, it is advisable to avoid giving real-time emotion updates to the user themselves.

VI. Conclusion and Future Work

As analyzed by the review, some of the more common approaches being taken currently include Electroencephalography (EEG), Facial Recognition (FR), Speech Recognition (SR), Voice Recognition (VR), Heart Rate Variability (HRV), Electro Dermal Activity or Galvanic Skin Response (EDA or GSR), Respiration (RSP), Skin Temperature (SKT), and Electromyography (EMG). While the study highlighted various methods being used for emotion recognition, it was also stated that different approaches suit better for certain studies based on application area. Some methods perform better with the use of stand-alone sensors, while others are more efficient and accurate with a combination of sensors and the collected data. Data gathered by physiological sensors contains noise that can be moderated or completely eliminated in a lab based setup. While this assists in being the training set, it has a tendency to reduce performance accuracy outside of a lab-based setup. Another point raised was that most real-world means of gathering emotion data using wearable like smartwatches collect data over a long time period; while most studies on the other hand, focus on shorter time periods like minutes or seconds. This shows that there is still a gap emotion data collected over a long time period and real-world emotion recognition. Adding on, most studies so far have had very few test subjects, due to which there the classifier performance is relatively poorer than if there were a larger sample size.

Many of the more common ER methods focus on outward expression, such as facial recognition and speech recognition. We must take into account the fact that a person who is happy might not be smiling, and a person who is sad might not be frowning, they could even be smiling. To tackle this gap, there needs to be further focus toward a potential solution that could analyze and perceive human emotions with implicit, close to no or very minimal user input or interaction. The implications of age based cognitive impairment as well as additional stressors like the inability to verbally express emotion or being bedridden need to be taken into account.

Moving forward, with our conceptual framework we will be looking into using a combination of physiological factors than are most effected by age related cognitive decline to detect and recognize user emotions, particularly negative emotions like depression. We aim to use minimally intrusive means of data gathering from the user. With this approach our goal is to propose a more autonomous emotion recognition-based monitoring system for the elderly.

Further on the aim is to carry out a case study on families of geriatric people living on their own and their families for pre- and post- implementation effectiveness and feasibility.

References

[1] WorldHealthOrganization, Mental health of older adults, 2017, https://www.who.int/news-room/fact-sheets/detail/mental-health-of-older-adults, accessed 12/09 2019.

[2] Gottfries C.G., 'Is there a difference between elderly and younger patients with regard to the symptomatology and aetiology of depression?', Int Clin Psychopharmacol, 1998, 13 Suppl 5, pp. S13-18.

[3] Grunberg, J.: '"Pedogeriatrics": a pediatric nephrologist's outlook on common challenges facing pediatric and geriatric nephrologists', Int Urol Nephrol, 2010, 42, (1), pp. 253-257.

[4] Hamdy, R.C., Lewis, J.V., Kinser, A., Depelteau, A., Copeland, R., Kendall-Wilson, T., and Whalen, K.: 'Too Many Choices Confuse Patients With Dementia': 'Gerontol Geriatr Med' (2017).

[5] C.-C. Hsu and Y. Y. Chien. (2009). An Intelligent Fuzzy Affective Computing System for Elderly Living Alone - IEEE Conference Publication. Available: https://ieeexplore-ieee-org.ezproxy.lib.uts.edu.au/document/5254356.

[6] Chen, Y. & Shen, C. 2017, 'Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition', IEEE Access, vol. 5, pp. 3095-110.

[7] Ghosh, A., and Riccardi, G.: 'Recognizing Human Activities from Smartphone Sensor Signals', in Editor (Ed.)^(Eds.): 'Book Recognizing Human Activities from Smartphone Sensor Signals' (ACM, 2014, edn.), pp. 865-868.

[8] Luštrek, M., Cvetkovic, B., Mirchevska, V., Kafalı, Ö., Romero, A., and Stathis, K.: 'Recognising lifestyle activities of diabetic patients with a smartphone', in Editor (Ed.)^(Eds.): 'Book Recognising lifestyle activities of diabetic patients with a smartphone' (IEEE, 2015, edn.), pp. 317-324.

[9] Quiroz, J.C., Yong, M.H., and Geangu, E.: 'Emotion-Recognition Using Smart Watch Accelerometer Data: Preliminary Findings', in Editor (Ed.)^(Eds.): 'Book Emotion-Recognition Using Smart Watch Accelerometer Data: Preliminary Findings' (ACM, 2017, edn.), pp. 805-812.

[10] Boustani, M., Schubert, C., and Sennour, Y.: 'The challenge of supporting care for dementia in primary care.', Clinical interventions in aging, 2007, 2, pp. 631-636 .

[11] Shu, L., Xie, J., Yang, M., Li, Z., Liao, D., Xu, X., and Yang, X.: 'A Review of Emotion Recognition Using Physiological Signals': 'Sensors (Basel)' (2018).

[12] Virtanen, M., Singh-Manoux, A., Batty, G.D., Ebmeier, K.P., Jokela, M., Harmer, C.J., and Kivimäki, M.: 'The level of cognitive function and recognition of emotions in older adults', 2019.

[13] Wiechetek Ostos, M., Schenk, F., Baenziger, T., and von Gunten, A.: 'An exploratory study on facial emotion recognition capacity in beginning Alzheimer's disease', Eur Neurol, 2011, 65, (6), pp. 361-367.

[14] Park, S., Kim, T., Shin, S.A., Kim, Y.K., Sohn, B.K., Park, H.-J., Youn, J.-H., and Lee, J.-Y.: 'Behavioral and Neuroimaging Evidence for Facial Emotion Recognition in Elderly Korean Adults with Mild Cognitive Impairment, Alzheimer's Disease, and Frontotemporal Dementia.', Frontiers in aging neuroscience, 2017, 9, pp. 389.

[15] Ding, Y.v.K., Yasmin van, K., Dana, B., Qing, Z., Mohan, K., and Hang: 'Understanding Smart Home Sensor Data for Ageing in Place Through Everyday Household Routines: A Mixed Method Case Study', JMIR Mhealth Uhealth 2017;5(6):e52 https://mhealth.jmir.org/2017/6/e52/, 2017.

[16] Soroush, M.Z., Maghooli, K., Setarehdan, S.K. & Nasrabadi, A.M. 2017, A Review on EEG Signals Based Emotion Recognition.

[17] Thanh, C.K., Cécile, B., Jean Claude, B., and Nhan, L.: 'Emotion recognition using musical mnemotherapy with three physiological sensors', 2017.

[18] Benaissa, B., Ouml, Ppen, M., and Yoshida, K.: 'Activity and Emotion Recognition for Elderly Health Monitoring', International Journal of Affective Engineering, 2017, 17, (2), pp. 81-88.

[19] Lee, U., Snider, D., Quiroz, J.C., Geangu, E., and Yong, M.H.: 'Emotion Recognition Using Smart Watch Sensor Data: Mixed-Design Study': 'JMIR Ment Health' (2018).

[20] Jamil, N., Khir, N.H.M., Ismail, M., and Razak, F.H.A.: 'Gait-Based Emotion Detection of Children with Autism Spectrum Disorders: A Preliminary Investigation', in Editor (Ed.)^(Eds.): 'Book Gait-Based Emotion Detection of Children with Autism Spectrum Disorders: A Preliminary Investigation' (2015, edn.).

[21] Schneider, S., Christensen, A., Häußinger, F.B., Fallgatter, A.J., Giese, M.A., and Ehlisa, A.-C.: 'Show me how you walk and I tell you how you feel — A functional near-infrared spectroscopy study on emotion perception based on human gait', in Editor (Ed.)^(Eds.): 'Book Show me how you walk and I tell you how you feel — A functional near-infrared spectroscopy study on emotion perception based on human gait' (2014, edn.).

[22] Adib, F.: 'Household Radar Can See Through Walls and Knows How You're Feeling', IEEE Spectrum, 2019.

[23] Rozanska, A., Rachwaniec-Szczecinska, Z., Kawala-Janik, A., and Podpora, M.: 'Internet of Things Embedded System for Emotion Recognition', in Editor (Ed.)^(Eds.): 'Book Internet of Things Embedded System for Emotion Recognition' (IEEE, 2018, edn.), pp. 1-5.

[24] Leber, J.: 'An Atlas Of The Human Body That Maps Where We Feel Emotions', 2014.

[25] Hietanen, L.N., Enrico, G., Riitta, H., and Jari, K.: 'Bodily maps of emotions', 2013.

[26] Kadir, R.S.S.A., Murat, Z.H., Sulaiman, M.Z., Taib, M.N., Hanapiah, F.A., and Omar, W.R.W.: 'The preliminary investigation of electromagnetics radiation for the left hemisphere stroke', in Editor (Ed.)^(Eds.): 'Book The preliminary investigation of electromagnetics radiation for the left hemisphere stroke' (IEEE, 2014, edn.), pp. 606-610.

[27] Kadir, R.S.S.A., Murat, Z.H., Taib, M.N., and Jalil, S.Z.A.: 'Investigation of electromagnetics radiation for stroke patients and non-stroke participants - IEEE Conference Publication'. Proc. Control and System Graduate Research Colloquium (ICSGRC), 10-11 Aug 2015.

[28] Murat, Z.H., Kadir, R.S.S.A., Kamaruzaman, N., and Rosdi, M.: 'Down syndrome and non-down syndrome: Electromagnetic radiation for the physical and psychological conditions', in Editor (Ed.)^(Eds.): 'Book Down syndrome and non-down syndrome: Electromagnetic radiation for the physical and psychological conditions' (IEEE, 2015, edn.), pp. 127-132.

[29] Zhao, M., Adib, F., and Katabi, D.: 'Emotion recognition using wireless signals'. Proc. Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking, New York City, New York2016.

[30] Barrett, L.F., Adolphs, R., Marsella, S., Martinez, A.M., and Pollak, S.D.: 'Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements', Psychological Science in the Public Interest, 2019, 20, pp. 1-6.

[31] Wang, S., He, M., Gao, Z., He, S., and Ji, Q.: 'Emotion recognition from thermal infrared images using deep Boltzmann machine', Frontiers of Computer Science, 2014, 8, pp. 609-618.

[32] Sivapalan, S., Denman, S., Fookes, C., and Sridharan, S.: 'Human Identification in Video Surveillance Using Improved Gait Recognition Approaches – Speech, Audio, Image and Video Technology', 2017.

[33] Yaddaden, Y., Bouzouane, A., Adda, M., and Bouchard, B.: 'A new approach of facial expression recognition for ambient assisted living', in Editor (Ed.)^(Eds.): 'Book A new approach of facial expression recognition for ambient assisted living' (Association for Computing Machinery, 2016, edn.).

[34] Egger, M.L., Matthias; Hanke, Sten;: 'Emotion Recognition from Physiological Signal Analysis: A Review', Electronic Notes in Theoretical Computer Science, 2019, 343, pp. 35-55.

[35] Hairston, W.D., Whitaker, K.W., Ries, A.J., Vettel, J.M., Bradford, J.C., Kerick, S.E., and Kaleb, M.: 'Usability of four commercially-oriented EEG systems - IOPscience', 2014.