AUTOMATED EVALUATION SYSTEM OF STRESS IN CATTLE

By

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A thesis in fulfilment of the requirements for the degree of

Doctor of Philosophy

School of Biomedical Engineering

Faculty of Engineering and Information Technology

University of Technology Sydney

February 2020

CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This research is supported by the Australian Government Research Training Program.

Mohammed Ahmed Jaddoa

February 2020

ACKNOWLEDGEMENTS

First and foremost, all praise is to the almighty ALLAH (s.w.t) for helping and supporting me during my long journey in PhD study.

I would like to express my very great appreciation to my supervisor Assoc Prof. Adel Al Jumaily for his limitless support, suggestions and encouragement, which have guided me to overcome challenges more successfully. In addition, I am grateful for his effort for reviewing my writing and correcting the mistakes that have led me to publish my research in high-quality conferences and journals. Special thanks to my external co-supervisor Assoc Prof. Luciano Gonzalez for his assistance through providing me imaginary and physiological datasets; without this help, I could not have conducted my research. Also, sincere thanks to my colleague Miss. Holly for sharing her knowledge and experience regarding health issues of cattle, which is the essential part from my research.

I extend my gratitude to my youngest brother Ali for his assistance in preparing an imaginary dataset. Many thanks also go to all my friends at University of Technology Sydney (UTS) in Australia. My close friends Firas, Mahmood, Abdul Wahed, Ahmed, Hassen, Bilal, Nizzar, Abood and all the staff who have helped me at UTS, Sydney campus.

Words are not enough to express my appreciation and feeling toward my parents Ahmed Jaddoa and Saadiyah Ismael for their love, support, encouragement and patience throughout my PhD study. Also, special gratitude to my siblings Sura, Yassir, Mustafa and Israa.

Lastly, many thanks go to the Iraqi government (Ministry of Higher Education and scientific research-University of Anbar) for sponsoring me financially through the PhD.

ABSTRACT

Stress in animals can be defined as internal and external body response to environmental effects. Stressed cattle after slaughtering produce meat with less than the normal amount of glycogen with undesirable taste and colour, which is called 'dark meat’. Dark meat is not appropriate for human consumption which causes massive economic losses in the global meat industry. Cattle under stress exhibit high metabolic rate, heart rate, respiration rate, and skin temperature. These physiological changes have been used in many studies as stress indicators for measuring stress in cattle before slaughtering such as blood tests and rectal temperature. These current measurement methods are invasive and are considered as wasting time and effort when dealing with a very large number of cattle on a farm. Several researchers used Infrared thermography technology (IRT) as an alternative non-invasive method for detecting stress pre-slaughtering through measuring temperature for eyes region. So far little research has been carried out to detect pre-slaughter stress automatically in cattle with dark-meat prediction. Therefore, the main aim of this research is to develop a new fully automated system for detecting stress pre-slaughtering and predicting dark meat.

Multi-view face detection in cattle with enhancement of the accuracy of detection rate. Multi-view face detection is achieved through using three Support Vector Machine (SVM) classifiers, which are established by using Histogram Oriented Gradient (HOG) as features and SVM for classification. Detected face is used as the Area of Interest for eyes segmentation.

A novel segmentation approach to automatically identify the eyes of cattle regardless of the position of the animal in relation to the camera. This proposed novel method includes foreground identification using edge difference. A new method for thresholding based on histogram processing is also proposed. After eye segmentation, eye localization and temperature measurement will be the last stage of the proposed method.

Lastly, Support Vector Machine (SVM), Logistic Regression (LR), Naïve Bayes (NB), Decision Tree (DT) are developed as machine learning algorithms for stress assessment and predicting dark-cutting. The results show that the proposed system based on the Decision Tree model can be used to detect stress with a dark-meat prediction with significant accuracy in term of Specificity, Recall and F-measure.

DEDICATION

To who gave me endless love support and encouragement my parents: ***Ahmed Jaddoa and Saadiyah Ismael***

Also, To my beloved supervisor: ***Assoc.Prof. Adel Al-Jumaily***

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THESIS ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neural Network
e-Health	Electronic Healthcare
F1	F1 Score
FN	False Negative
FP	False Positive
IRT	Information Technology
IT	Infrared Thermography Technique
KNN	k-nearest Neighbours Algorithm
LNN	Linear Neural Network
ML	Machine Learning
MLP	Multi-Layer Perceptron
RL	Receiver Operator Curve
ROC	Reinforcement Learning
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
VSM	Vital Signs Monitor
WSN	wireless sensor networking

LIST OF PUBLICATIONS

Journal Paper (Under review):

M. A. Jaddoa, A. Al-Jumaily, L. Gonzalez and H. Cuthbertson, “Novel automatic eyes segmentation in cattle based on intensity features and edge processing using infrared thermography images”. URL: https://link.springer.com/journal/11042 Paper Submission: 16 April 2019

Conference Paper:

M. A. Jaddoa, A. Al-Jumaily, L. Gonzalez and H. Cuthbertson, "Automatic eyes localization in thermal images for temperature measurement in cattle”, 12th International Conference on Intelligent Systems and Knowledge Engineering URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8258765&isnumber=8258711.

Jaddoa, M.; Al-Jumaily, A.; Gonzalez, L. and Cuthbertson, H. (2019). Automatic Temperature Measurement for Hot Spots in Face Region of Cattle using Infrared Thermography. In Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics - Volume 1: ICINCO, ISBN 978-989-758-380-3, pages 196-201. DOI:10.5220/0007810101960201,URL:https://www.scitepress.org/PublicationsDetail.aspx?ID=s1eU9W7jntE%3d&t=1.

Book Chapter:

M. A. Jaddoa, Cuthbertson H, Al-Jumaily A. Multi View Face Detection in Cattle Using Infrared Thermography. In Applied Computing to Support Industry: Innovation and Technology: First International Conference, ACRIT 2019, Ramadi, Iraq, September 15–16, 2019, Revised Selected Papers 2020 Jan 7 (Vol. 1174, p. 223). Springer Nature

Chapter 1 Introduction

1.1 Introduction

Several studies have been conducted to test the health and physiological status of animals by using different kinds of measurements such as blood test, rectal temperature, respiratory rate and heart rate [1]. By using these methods, beneficiaries from these kinds of measurements will be sure of an animal's health and physiological status of the animal through interpretation of captured data. One of the important measurements is body temperature. Irregular body temperature can be considered as a biological mark of disease in an animal [2], inflammation [3] and physiological status [4]. By using traditional methods for measuring temperature, animal owners need to be physically close to the animal. In addition, traditional methods are time-consuming because all animals need to be tested individually by a human.

There are some restrictions associated with this technology that needs from users to take care with while taking an image by using the IRT camera. These factors include sunlight, high humidity as well as heat loss because of the wind or when the surface of the body is dirty. In addition, the emissivity of radiation for objects and reflection (connectivity with another object) of radiation that comes from other objects are also considered as other factors that affect the accuracy of captured results by an infrared camera [5]. Moreover, a dirty surface of the body will provide different radiation from the clean surface which means a different temperature in both cases [1]. However, the significant factors or parameters that are required to be provided to the camera are: emissivity of the object, reflected radiation, the distance between the object and camera and humidity [5]. IRT has different applications in many areas as well as industry such as human and veterinary medicine [6, 7]. The importance of IRT is that there is no need for physical contact with the imaged target, and it can provide temperature distribution of scanned surface remotely [7]. Table 1.1 below shows the IRT camera used in this research with its details.

Table 1. 1: Infrared camera models [8]

Author	Model	Infrared resolution (pixels)	Thermal precision	Thermal sensitivity	Minimum focus distance
Menegassi et al. (2015)	FLIR T300	320 × 240	+/−2 °C	<0.05 °C at 30 °C	0.4 m
Cruz Júnior et al. (2015)	FLIR T300	320 × 240	+/−2 °C	<0.05 °C at 30 °C	0.4 m
Cook et al. (2015)	FLIR A320	320 × 240	+/−2 °C	<0.05 °C at 30 °C	0.4 m
Talukder et al. (2014)	FLIR T620	640 × 480	+/−2 °C	<0.05 °C at 30 °C	0.25 m
Alsaaod et al. (2014)	FLUKE Ti25	640 × 480	+/−2 °C	⩽0.09 °C at 30 °C	0.15 m
Simões et al. (2014)	FLUKE Ti9	640 × 480	+/−2 °C	⩽0.09 °C at 30 °C	0.15 m
Soerensen et al. (2014)	FLIR SC660	640 × 480	+/−1 °C	<30 mK at 30 °C	0.2 m
Paim et al. (2012), Martins et al. (2013)	FLIR i3	60 × 60	+/−2 °C	<0.15 °C at 25 °C	0.6 m
Abudabos et al. (2013)	VisIR-Ti200	640 × 480	+/−2 °C	<65 mK at 30 °C	?
Valera et al. (2012)	FLIR i70	140 × 140	+/−2 °C	<0.08 °C at 25 °C	0.12 m
Weschenfelder et al. (2013)	FLIR i60	180 × 180	+/−0.1 °C	<0.1 °C at 25 °C	0.10 m
Ferreira et al. (2011)	Testo 880	320 × 240	+/−0.1 °C	<0.1 °C at 30 °C	0.10 m
Pezeshki et al. (2011)	FLIR E2	160 × 120	+/−2 °C	0.12 °C at 30 °C	0.3 m
Polat et al. (2010)	FlexCam S	?	+/−2 °C	<0.09 °C at 30 °C	?
Stubsjoen et al. (2009)	InfraCam SD	120 × 120	+/−2 °C	<0.1 °C at 25 °C	0.3 m
Rainwater-Lovett et al. (2009)	FLIR EX320	320 × 240	+/−2 °C	<0.08 °C at 25 °C	?
Montanholi et al. (2008, 2009)	FLIR SC2000	320 × 240	+/−2 °C	<0.05 °C at 30 °C	0.30 m
Fonseca et al. (2006), Van Hoogmoed and Snyder (2002)	DTIS 500	320 × 240	?	?	?
Stewart et al. (2007)	FLIR S60	320 × 240	+/−2 °C	<0.10 at 30 °C	?
Nikkhah et al. (2005), Schaefer et al. (2004), Berry et al. (2003)	FLIR 760	175 × 131	+/−2 °C	<0.10 °C at 30 °C	0.5 m
Holmes et al. (2003)	FLIR PM-280	256 × 256	+/−2 °C	<0.07 °C at 30 °C	?

As shown in this table above, the resolution has represented the quality of the camera, and thermal precision is the accuracy of the camera, while thermal sensitivity refers to a percentage, and finally the distance between the target object and camera. Emissivity factor was mentioned with following values 0.98[9-11], 0.97[6, 12], 0.95[13, 14],0.93 [15] and 0.86 [16]. Some of the researchers installed the IRT camera in a water station which leads to obtaining high quality data in a way that does not disturb the animal[17].

1.2 Research Problem

There are different factors that cause stress in an animal before moving from the farm to the abattoir. These factors include contact with humans, the circumstances of transportation, experience of living in a new environment, lack of water and food, social changing among animal group such as mixing or isolation and variations in weather. In addition, these factors could develop into fear, thirst and starvation, excess of physical activity and exhaustion and physical injury, and if unsolved these impacts can lead to increase in psychological stress. Stress is one of the reasons that leads to decrease in the amount of glycogen in muscles in animal which is called dark meat. Before slaughter, animals that face stress are likely to have dark meat post-slaughter [18].

As a response to stress, inside an animals body there is an increase in concentration of cortisol in animal blood associated with elevated body temperature. Rising of cortisol in blood has a correlation with an increase of cortisol in saliva [2]. Thus, measurement of body temperature and cortisol in saliva leads to evaluation of the stress in an animal.

Some studies showed that small areas around the posterior border of the eyelid and caruncle lacrimal of eyes are a good indicator of stress [19]. This area is easy to affect with blood flow with temperature changes due to its rich thin veins that are associated with the sympathetic system [1]. In some animals like horses, there is significant correlation with increasing eye temperature with both salivary and plasma cortisol [4]. In consistent with this study, researchers [20] found that a horse during Jumping competition has a high rate of stress which results in a high value of eye temperature, and this result is matched with the salivary cortisol level.

By measuring the temperature of eyes, meat producers can know if an animal is under stress or not. Several types of cameras have been used to capture Infrared Thermography images with attention to distance, thermal sensitivity and thermal precision. Captured Infrared images analysed by using different software such as FLIR, FLUKE and INFRACAM have been used to analyse infrared images for temperature measurement as demonstrated in Table 1.1. After analysing Infrared images, meat producers can be sure whether an animal is under stress or not. Software Users need to analyse every image by using this software and it is time consuming. Nowadays, there is no software or system that analyses an image automatically without human intervention and provides results automatically if an animal is under stress or not. Therefore, this PhD research focuses on developing a universal system for evaluating stress status of cattle by measuring temperature of eyes automatically using image processing and machine learning technologies of Infrared Thermography images.

1.3 Research Questions and Objectives

The following research questions are addressed in this thesis.

1- Is it possible to evaluate stress of cattle without human intervention?
2- How to decide if cattle are under stress?
3- How to evaluate the performance of the proposed system for stress evaluation?
4- How to localize eyes region automatically?

In order to address these questions, the next sections, research objectives and contributions, will provide more details.

This research aims to build an automated system for evaluating stress in cattle pre-slaughtering based on image processing techniques and machine learning algorithms. More specifically, stress detection automatically for cattle leads to prevent dark meat after slaughtering. In order to achieve the main research aim in this thesis, several objectives are identified below.

1. To explore different techniques based on automated systems for medical diagnosis based on machine learning, computer vision and infrared thermal processing.
2. To collect a dataset of physiological and thermal data for cattle with different gender and age, including physiological data collected for cattle after slaughtering, and thermal data collected before slaughtering.
3. To propose the Multi-view face detection method in cattle, which can detect the face region in different positions and orientations of the cattle's body.
4. To develop automatic eyes segmentation based on infrared thermal image processing.
5. To design machine learning models based on thermal features for detecting stress and the best model with high performance and accuracy chosen from: Support vector machine, Logistic regression, Naive Bayes, and Decision Tree.
6. To evaluate the performance of proposed methods using assessment metrics from two perspectives, statistical techniques (Sensitivity, Specificity, Recall, F1 measures) and visualization techniques (Receiver operating characteristic (ROC), and the Area under the ROC curve (AUC)).

1.4 Research Contributions

This study proposes a novel system for evaluating stress in cattle pre-slaughtering in order to avoid dark meat after slaughtering. Our technique offers a robust methodology for pre-processing thermal data, face detection, segmentation, features selection, and classification using image processing and machine learning algorithms. On this aspect, the following contributions are made as follows:

- The proposed research provides a system that shifts from manual methods for evaluating stress to an automated intelligent approach. The system is able to examine stress in each animal automatically, remotely and non-invasively.
- A new face detection method is achieved, which has the ability to detect the face region of cattle in different positions and orientations with high performance and accuracy. In addition, the main aim of this method is identifying the face region.

- Automatic eyes segmentation is achieved in order to localize eyes region and extracting temperature from eyes. Extracted temperature from eyes is used as a feature, which is employed for building machine-learning models.
- Using advanced machine-learning models to analyse temperature features for the classification purposes. In this research, 4 machine-learning models have been evaluated and the study has provided a detailed assessment of their prediction abilities to classify two classes: healthy and stress in cattle.

1.5 Research Significance

This research aims to develop a system for evaluating stress of an animal. The main benefit from developing this kind of system is improving the production in the meat industry by minimizing stress pre-slaughter and avoiding producing dark meat. It is essential for meat producers to recognize the stress status of an animal before slaughter that will lead to treatment and produce fresh meat. The proposed system is expected to improve the performance of the meat industry and improve the ability to assess animal welfare [1].

1.6 Thesis Structure

The thesis is divided into 7 chapters, each chapter covering a specific area of the research work. The contents of this thesis are organised as follows:

- **Background and Literature Review (Chapter 2):** This chapter discusses what stress in cattle is, the common impacts of stress, the correlation between stress and dark meat. This is followed by a discussion on other impacts and risk factors related to stress. Also, the role of infrared thermal technology in detecting stress via extracting temperature, and the current used methods based on infrared thermal for detecting stress.
- **Machine Learning, Computer Vision, and Image Processing (Chapter 3):** This chapter discusses and reviews all methodologies that used infrared thermography technology in image processing, computer vision and machine learning as well as automated diagnosis system based on infrared thermography. Several methods based on infrared thermography are reviewed, which used eyes segmentation and localization, face detection. In addition, several automated systems based on infrared thermography are reviewed that are used for detecting fever, infection and stress. About the machine learning models, learning algorithms, and classification techniques are discussed and

reviewed. Furthermore, the review provides an idea of the statistical techniques using in data analysis that are utilised to complete this empirical study. The last part is the proposed methodology for detecting stress in cattle. The components of the proposed method are explained in detail. Finally, there is an overview of the chapter.

- **Multi-view Face Detection in Cattle (Chapter 4):** This chapter presents the proposed methodology for detecting the face region in cattle with several views, orientations and positions of cattle's body. In this chapter, it discusses data preparation process and the current used methods for face detection with their limitations. Multi -view face detection is proposed to fully address limitations of current used methods. Evaluation Techniques for performance techniques metrics (Sensitivity, Specificity, F1-Measure, Accuracy, and Detection rate) are also illustrated in this chapter. Experimental results for the proposed methodology are also discussed with a comparison of the currently used method in this literature. Lastly, the chapter provides a summary about the proposed methodology.
- **Automatic Eyes Segmentation in Cattle (Chapter 5):** This chapter presents the proposed methodology for automatic eyes segmentation in cattle. The components of the proposed method explained in detail. Evaluation Techniques for performance techniques metrics (Sensitivity, Precision, F1-Measure, Accuracy, and Misclassification) are also explained in this chapter. Based on experimental results, comparison is made with three well-known automatic segmentation methods, and results are discussed. Lastly, the chapter ends with a summary about the proposed methodology.
- **Stress Detection in Cattle (Chapter 6):** This chapter presents the methodology for stress detection based on machine learning algorithms. In this chapter, it discusses dataset preparation, cleaning and features selection. Four machine learning algorithms are explained and built. Evaluation Techniques for performance techniques metrics (Sensitivity, Precision, F1-Measure, Accuracy, AUC, and ROC) are also explained and used in this chapter. Experimental results for each machine learning model are discussed based on performance evaluation metric. The chapter ends with conclusion and summary of the chapter
- **Conclusion and Future works (Chapter 7):** The conclusion section presents the entire research and discusses its outcomes. This chapter explains the limitations on the methodology and experimental set-up and outlines future work.

Chapter 2   Background and Literature Review

2.1   Introduction

In 2014, the number of cattle has been rising globally and has reached 1.5 billion [21, 22]. It is estimated that the number of cattle will increase significantly and reach 1.8 billion in 2030[23]. In Australia, the number of cattle was enough only to supply the local population[24]. Over the past decade, the number of cattle has increased largely and reached 25 million, which represent 2% from global cattle population[25]. As a result of this growth, the number of cattle with related industry becomes of an important economic value for the Australian economy in general and the agricultural sector specifically[26]. Several factors have a significant effect on the success of the cattle industry ;these factors include production chain, management, international trade, animal health and welfare, and consumers demands[27]. Consumers in several countries are concerned about cattle management, cattle welfare, as well as meat quality[28].

In Australia, consumers would like to pay more in order to obtain meat with high quality[29, 30]. These consumer concerns have motivated many researchers in order to address the reasons that reduce meat quality. Extensive research emphasises the impacts of stress in cattle pre-slaughter, and its correlation with meat quality. Several methodologies have been used to evaluate stress in cattle[31], sheep[32], and pigs[33]. These methodologies are invasive and time-consuming, and costly as well as being impractical when have a very large number of animals. For these reasons, new technologies are being adopted for assessing stress in farms and slaughterhouses[34].

This chapter presents the past and current literature of stress in animals and cattle, impacts of stress on meat quality and stress diagnosis using infrared thermal. In this chapter, different infections and inflammations are reviewed, which are diagnosed using infrared thermal. After that, stress and its relationship with dark meat is investigated deeply. Chapter ends with a conclusion section.

2.2 Literature review protocol

The research scope of this chapter is established by using the keywords stress, dark-cutting, meat quality, dark meat and dark firm dry. These keywords are used to search target articles in academic digital databases: Science Direct, Scopas, IEEE Xplore, Web of Science and Google scholar. Several academic journals and conferences are downloaded and studied extensively. These articles are related to invasive and non-invasive methods for detecting stress in general as well as dark meat. Afterwards, other keywords are used for seeking non-invasive methods for detecting stress, which included Infrared, thermal, thermography, Infrared thermography, camera and stress. The last stage is searching about automated non-invasive system or method dealing with stress and dark meat. For this target, keywords used are system, automated, automation, prediction, model, machine learning and framework. These keywords combine with stress, dark meat and infrared thermal as well as alternative terms. Combination with keywords were achieved using ‘OR’ and ‘AND’. Reports and white paper are excluded from this chapter. In addition, articles that outside of the research scope.

2.3 Meat quality

Meat quality has a direct impact on consumer intention for purchasing beef products[35]. Eating quality is the most significant factor that influences 65% of the consumers' attitude towards purchasing[36] . Also, consumers in many countries are willing to pay more in order to obtain meat with high eating quality[29]. Beef consumption decreased noticeably in Australia in 1990 as a result of bad eating experiences [37]. For this reason, Meat Standards Australia (MSA) is proposed as a program for identifying meat quality and observing consumers’ experience with eating quality when meat is cooked [37, 38]. Many studies have been conducted to determine the effect of the factors on meat and eating quality. These factors are ultimate pH, muscle glycogen, pre-rigor temperature and sarcomere shortening[39-41]. The most well-know factors are PH and meat color.

2.3.1 PH

Ultimate PH and meat colour have been known as a significant indicator of meat quality [28]. The changing in meat quality such as colour, microbial growth, shelf-life, flavour, lipid oxidation and tenderness is associated with increasing of PH [42]. Meat with high quality is directly linked with normal PH which is in the range 5.4-5.7. MSA stated that meat with PH range 5.8-6.0 has less tenderness, which is not desirable for consumers [43, 44]. In the stage

PH above 6.0, meat colour tends to be quite dark due to retaining water and close to spoilage. Also, taste can be described as bland [28, 42]. The phenomenon of meat with PH above 6.0 is called 'dark, firm, dry' (DFD), 'dark-cutting' (DC) meat or Dark meat(DM)[45].

2.3.2 Meat colour

Meat colour is a visual quality feature which affects consumer's attitude greatly toward purchasing meat in butcher shops or meat market [42, 46]. The colour gamut of meat can be classified as a consequence of the combining between myoglobin (red hue), deoxymyoglobin (purple hue) and metmyoglobin (brown hue)[42, 47]. The constancy of the meat colour is affected by oxidative state of myoglobin[47]. Factors include the presence of oxygen, metal ions, the high or fluctuating temperature during storage, pH of the meat and the microflora lead to oxidation of deoxymyoglobin or oxymyoglobin to metmyoglobin, which causes a change in meat colour [47]. Undesirable meat colours have a substantial cost for the meat industry. According to MSA, dark meat or dark-cutting cost $35 million in each year in Australia [46, 48]. This cost computation is for 40% of carcasses graded by MSA, but the cost is higher if non-MSA carcasses are added [49]. In addition, the cost for treating dark meat carcass is approximately $100-400 per carcass [46]. The economic impacts of meat colour have motivated the beef industry to investigate the factors that influence meat colour [46, 47]. It is crucial to reduce or prevent Dark-cutting or Dark meat in beef carcasses or to have any tool to predict which animal will produce Dark-cutting after slaughtering.

2.4 Meat quality and stress pre-slaughtering

The stress pre-slaughtering has a negative effect on ultimate pH (pHu), muscle glycogen, rigor temperature and colour, which impact on meat quality as a last outcome [28, 45, 46, 48, 50]. In addition, it found that PH impacts negatively on eating quality [51]. In the next sub- sections, impacts of stress on meat and eating quality are explained in detail.

2.4.1 Impacts of stress pre-slaughtering on PH, colour, and dark meat

Stress pre-slaughtering leads to minimize muscle glycogen with high rate PH, which is highly correlated to dark meat [42, 52-54]. In contrast, normal PH is associated with increase in the proteins in the myofilaments with drop water from the myofibrils, which leads to meat with good quality [55]. Dark meat is a result of the stress that the animal faces during the slaughter procedures [42]. Dark meat has been occurred in the range 0.77% and 15% among countries that produce meat [42].

2.4.2 Impacts of stress pre-slaughtering on eating quality

Stress has been well-known as an important factor that impacts meat quality and eating quality [48]. Pre-slaughter stress has negative effects on tenderness, flavour and juiciness of meat, along with the shelf-life of meat [50, 51]. The main reason for the stress drawback is reducing of glycogen in muscles, which is caused by the surge in catecholamine secretion, and it occurs as a physiological response to stress[54, 56, 57]. Dark meat has low eating quality, for instance meat with high PH has a higher rancid flavour in meat[58]. In addition, dark meat has lower rating in tenderness, juiciness, flavour and liking [51].

2.5 Stress physiology in animals

Stress in an animal can be defined as internal and external body response to environmental effects [59]. In the animal farm, dairy cows that are involved in a stressful situation have the following changes in their bodies [1]. Hypothalamic-pituitary-adrenal (HPA) will provide hormones called plasma corticosteroids as a physiological response to stress. Other changes are caused by stress: the sympathetic nervous system of the animal activates, heart rate increase, adrenaline (epinephrine) is produced, and blood flow is redistributed to skeletal and heart to formulate animal physiologically for fight or flight[2]. There are several factors that can produce stress in an animal. These factors include contacting with humans, the circumstances of transportation, experience of living in a new environment, lack of water and food, social changing among animal group such as mixing or isolation and variations in weather. In addition, these factors could develop to produce the following cases of fear, thirst and starvation, excess of physical activity and exhaustion and physical injury, and unsolved, these impacts can lead to increase in psychological stress[18]. As a response to the stress situation, metabolic rate, heart rate, respiration rate, and skin temperature increase [60]. These physiological changes have been used as stress indicators for measuring stress in animals [61].

2.6 Physiological indicators of stress in animal

The physiological reaction to stress situations has been widely used to evaluate stress in an animal [62]. Heart rate (HR), respiration rate (RR), body and skin temperature have been used as stress indicators to detect stress in several animal species [63]. It is shown that HR is increased as an outcome from disturbing situations [64]. The rise of HR has been associated with escaping from stressful situations when animals feel danger [33, 63]. For instance, it was noticeable that there was 130% rise in HR when sheep were gathered using a shepherd and a dog [64]. Several researchers have used HR as an indicator when an animal has lived in an environment with poor handling and facilities. There is a high correlation with cortisol levels in cattle and HR, and HR is also correlated with vocalization in pigs [65]. Other studies have shown that HR is lower (82.3 bpm) when sheep are housed in metabolic cages, and HR is raised when sheep are housed in 'common enclosure' and 'fixed housing'(85.7 and 84.8 bpm respectively)[66]. Another stress indicator is respiration rate (RR), which rises as a response to physical activity, heat stress, and stressful situations [33]. Based on empirical results, it is suggested that RR is a good stress indicator for cattle to detect short time stress [67]. In addition, RR is a good stress indicator for an animal facing heat stress [68, 69]. Animals under stress faced change in body temperature as the response of the autonomic nervous system (ANS)[70]. Body temperature increase in pigs, rabbits, cattle and sheep is a response to stressful situations as well as in other animals [33, 54].

2.7 Invasive techniques for measuring stress indicators

Several invasive techniques are used to examine stress indicators such as changes in cortisol, heart rate (HR), body temperature, respiration rate [71].Animals under stress faced increasing cortisol concertation in blood , and measuring cortisol in blood can be used as an invasive method for stress detection [72].Measuring cortisol in saliva was suggested by several researchers for evaluating stress in animals [73]. The problem with using cortisol measurement is it takes a long-time for analysing in laboratories by experts, which is not practical for real-time evaluation [74, 75].

As mentioned in section 2.5, changing in heart rate has been used as a physiological stress indicator. Many methods have been used to examine HR in animals under stress. The oldest method is using a stethoscope to measure heartbeat [34]. This device is required to be placed in the heart position, which required a skilled technician who has knowledge about the correct heart location in different species [34, 76]. Another method for measuring HR is electrocardiograms (ECG). Another stress parameter is body temperature, which can be measured by placing a thermometer [77] or a thermometric probe[78] in the rectum of an animal which is called rectal temperature. Rectal temperature was used in several animals, for example bovine and ovine [79]. The last stress indicator is RR that can be measured by direct observation or video-based observations for breathing movements [67, 80-82]. Another method for measuring RR is recording the time taken for 10 flank movements [80]. Stethoscope was also used to measure RR in animals [67]. Attaching breathing sensors in an animal's nose is used to measure RR[83].

2.8 Non-invasive techniques for measuring stress indicators

Even though the invasive techniques are useful for detecting stress indicators in animals, these techniques have disadvantages which need to be considered. Invasive techniques are requiring physical contact between human and animal. These techniques are time consuming and cost a lot if implemented on a large scale. For instance, having a large herd of cattle in a farm needs to have a large number of skilled technicians [84]. For these drawbacks, many researchers have investigated new non-invasive methods for evaluating stress indicators remotely and without contacting human with animal [1]. The most well-known used technique is image processing for infrared thermography images [84, 85]. The next section explains in detail the role of infrared thermography in detecting stress in an animal.

2.9 Stress evaluation using Infrared Thermography

Infrared thermal cameras or sensors have ability to obtain infrared radiation produced by objects and this radiation generated as image, which used to extract temperature. This extracted temperature used to assess the health status of human and animal [8]. Infrared thermal images used to measure temperature for eye region as alternative method instead of vaginal or rectal temperature, and results shown that eye temperature is correlated with changing core body temperature [84]. Many studies showed that small area around posterior border of eyelid and caruncle lacrimal of eyes are a good indicator of stress [19]. This area is easy to affect with blood flow with temperature changes due to its rich with thin veins that associated with the sympathetic system. There are significant changes in eye temperature after treatment and before treatment. In cattle, measuring temperature for eye region by IRT used for stress detection in case cattle face poor handling and facilities [84]. Isolation leads to rising eye temperature and human contact result in an increase of eye temperature [1]. In another animal like a horse, eyes temperature also related to signs of stress. As shown in the figure below, blood, saliva, and IRT eyes image samples collected in different durations in before and after challenge, and the results have demonstrated that significant correlation with increasing eye temperature with both salivary and plasma cortisol [86].In consistency with this study, Valera et al (2012) [20] found that horse during Jumping competition has a high rate of stress as a result of the high value of eye temperature, and this result matched with the salivary cortisol level. Horses after the competition, investigators have found that there is a significant correlation between the increased cortisol in blood and the growth of eyes temperature [2]. Horse during dressage process, there is belt tied under the chin and inside the mouth, this belt used to control the horse. Tide belt in a strong way around chin could cause an increase in eye temperature with decrease in the skin rounding eyes [87].

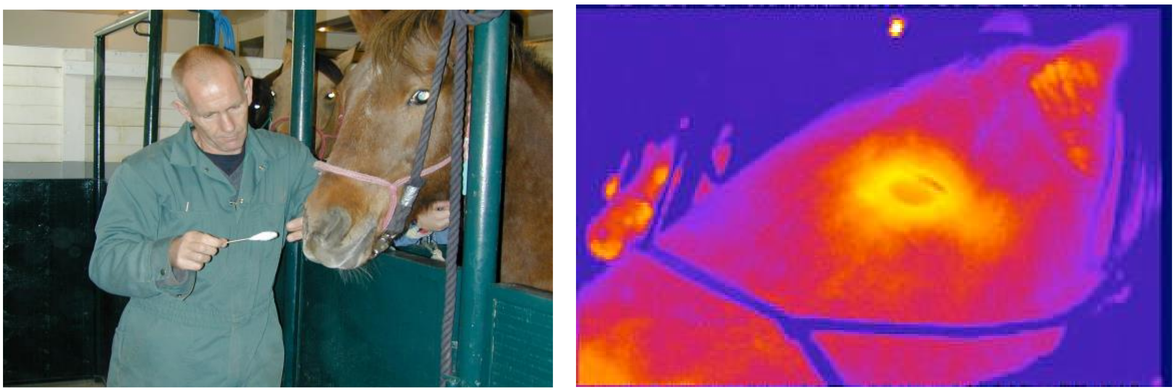


Figure 2. 1: Conventional method for stress evaluation[86].

As shown in Figure2.1, the picture on the left shows collection of saliva from the horses with cotton swabs for later analysis of the hormone cortisol via radioimmunoassay. The IRT image of the horse's eye is on the right [86]. There is also another role for eye temperature that is shown in the response of elk in a dehorning operation. Results showed that eye temperature increases when animal is not given a drug before removing the antlers. In this case, IRT can be used to detect fear and pain in cattle. It was noticed in cattle the decreases in eyes temperature as a response for electric prod, screaming and shocking [86]. In contrast, the eyes temperature is reduced in sheep as a response for stress[88].

The environmental conditions have stressful effects on the animal health, welfare, live weight and efficiency of animal's meat production. The stressful conditions include the feeling of being hot, cold and wet. The captured temperature by IRT for eyes, nose, and rump is a good indicator of heat stress and environmental comfort conditions. In addition to IRT, heart rates and body temperature of animals are shown whether the animal is under stress or not in regard to environment conditions such as heat [89]. The temperature of the foot, legs, and skin relies on blood flow, and blood flow is changing as a result of stress, and this altering will vary the amount of heat radiation in some regions of the animal body. For instance, the temperature of tail and paw in rate (measured by IRT) decreases in the fear situation [90]. Table 2.1 shows the summary of studies that used IRT for detecting stress.

Table 2. 1: Stress and correlation with temperature.

Author	Animal	Body region	Application	Temperature using IRT
(Vianna & Carrive 2005)	rat	tail and paw	Fear	Significant changes in tail and paw
(Stewart et al. 2007)	dairy cow	eye	Stress	High
(Church, Cook & Schaefer 2009) (Valera et al. 2012)	horse	eye	Stress	High after race
(Church, Cook & Schaefer 2009)	elk	eye	Fear	High in fear and after dehorning
(Stubsjøen et al. 2009)	Sheep	eyes	Stress	High
(Valera et al. 2012)	Horse	Eyes	Stress during jumping competition	High
(McGreevy, Warren-Smith & Guisard 2012)	Horse	Eyes	Stress during dressage process	High
[91] (Warriss et al. 2006)	pig	Ear	Stress	Significant changes
[9] (Weschenfelder et al. 2013)	Pig	Ocular Eyes as indicator for body temperature	Heat stress pre-slaughter	High
[92] (De Lima et al. 2013)	Rabbit	Ocular Eyes	Stress as response for environmental conditions	Significant changes as response for weather conditions

As shown in the table above, the temperature of different parts of the body increased as a response to stress and fear. According to previous studies, the mechanism of their methodologies was starting with measuring temperature before experimenting situation like heat stress, then measure temperature after the experiment, and computes the difference and the increased temperature after challenge.

2.9.1 Pre-slaughter stress detection using IRT and its impact on meat quality

Several studies confirm that eye temperature using IRT is correlated with meat quality. For instance, IRT images were used to measure temperature for eye region before slaughtering, and related extracted temperature to meat quality post-slaughtering. It was shown that IRT is a useful tool for predicting meat quality [9, 93]. In 2018, MLA organization in Australia conducted research about factors that create dark cutting. In this study, 120 cattle faced stressful situation pre-slaughtering. Infrared thermal camera was used to obtain temperature from eye region. RGB camera was used to obtain HR by obtaining changes of luminosity. After slaughtering, PH and meat colour were obtained from carcasses. The results showed that meat was dark with colour > 3 and PH > 5.7. In addition, there was a satisfactory correlation between dark cutting and HR and eye temperature [34].

2.10 Inflammation and Illness Diagnosis Based on IRT

Early diagnosis of the disease is the first step for successful treatment in the future [94]. One of the most valuable non-invasive tools that were seen by the researcher for this purpose is IRT; it is a useful tool for detection of inflammation, disease, and diagnosing pain by measuring temperature [95]. Rising temperature in a particular region can be considered a sign of inflammation or illness. In the other hand, the local pain reduced as the result of blood flow, edema or vascular thrombosis in inflamed tissues, and this leads to a decrease in temperature which results in an increase in an emission of thermography [8]. IRT has the ability also to detect laminitis (DD lesion infection) in dairy cows' feet by computing the difference of mean temperature between rear feet and front feet. The results showed that a foot with infectious DD lesions (inflammation) has a higher temperature than normal feet[13]. By using IRT, the temperature of hooves is higher in cows in early lactation stage than cows at the beginning of lactation stage[96]. In the horse, (Fonseca et al. 2006) conducted research about diagnosis back pain that is causes by thoracolumbar lesions. By using IRT in back regions, researchers revealed a hot spot in the back that caused pain and its affect on the horse' movement. IRT also can be used to detect the sign of foot-and-mouth disease virus (FMDV) in cattle by measuring the temperature of foot and mouth [97]. Poikalainen et al (2012) [98] pointed out that IRT is useful to detect injuries in feet, changing in temperature of leg part lead to estimate leg disorder by measuring the difference of temperature between hoofs and coronary band, and udder was not effected before and after milking that reflects the positive health of the animal. [6] Stated that IRT is a useful tool to detect mastitis in sheep. There is an increase in the temperature of the udder, especially in the subclinical stage. In cows, there is an increase of temperature in the udder that means infection or inflammation [15]. Polat et al (2010) [99] found out that IRT can detect the subclinical stage of mastitis in dairy cows. Automatic detection of mastitis system was developed commercially by using an IRT camera to monitor temperature status of a dairy cow's udder by early detecting mastitis before clinical signs show up (website company AgriCam caddi Mastitis). Animal owners will be warned by using this system.

IRT can also be used to detect early the clinical signs of BVDV infection by measuring the changes in temperature of eyes from several days to a week [100]. The researcher found out that temperature of eyes in an earlier stage of infection increase gradually in the first week. [17] found in conducted research that the eyes with the surrounding area can be used to determine calves with bovine respiratory diseases. Results were shown that infected calves have eyes with temperature more than 35.7 ± 0.35 C. IRT has also been used to detect early disease like musculoskeletal infections, orbital temperature measurement in calves [94]. Van Hoogmoed, and Snyder (2001) [101] stated that IRT was a good tool to evaluate which diagnosis method is useful to detect injury in feet, and this injury could be as a mark for a kind of disease. The results showed that in 62.5% of cases, IRT are helpful to identify the infected location. In humans, IRT has been used widely in a medical area like detecting tumor and cancer in the breast. It was found that the infected part with cancer has a higher temperature than a healthy part. IRT has also been used to evaluate environment by accounting ectoparasite in the animal skin in a coat [102]. Table 2.2 shows the infection and inflammation in animals and the relation with temperature.

Table 2. 2: Inflammation, Illness, and Correlation with Temperature

Author	**Animal**	**Body region**	**Disease Type**	**Temperature using IRT**
(Alsaaod et al. 2014)	Dairy cows	Feet	DD lesion infection	High (infected feet has higher temperature than healthy feet)
(Poikalainen et al. 2012)	Dairy Cows	areas with skin injuries	Injuries	High (injured area has higher temperature than surrounding)
(Martins, do Prado Paim, de Abreu Cardoso, Dallago, et al. 2013)	Sheep	Udder	Mastitis	High (for subclinical mastitis)
(Schaefer et al. 2007)	Beef cattle	eyes	BRDC virus	High
(Schaefer et al. 2012)	Beef cattle	Eyes and surrounding area	BRDC virus	High
(Schaefer et al. 2004)	Beef Cattle	facial areas include the side (lateral), back (dorsal) and hooves, the ears (mid-ventral area of the ear), nose (centre of hairless nose area) and eye with surrounding area with lachrymal gland plus the tear duct	BVDV virus type 2	Significant changes
(Pezeshki et al. 2011)	Dairy cattle	Udder	Inflammation	High
(Polat et al. 2010)	Dairy cattle	Udder	Subclinical mastitis	High
(Rainwater Lovett et al. 2009)	Cattle	Foot and mouth	foot-and-mouth disease virus (FMDV)	High temperature in foot
(Fonseca et al. 2006)	Horse	Back and thoracic regions of body	thoracolumbar lesions that cause back and chest pain which leads to lameness	High in Several spots in back body
(Nikkhah et al. 2005)	Dairy cattle	Hooves	Inflammation	High temperature in cows in early/mid-lactation stage

				than cows in late lactation stage
[103] (Berry et al 2003)	Dairy cattle	Udder	Mastitis	High temperature of udder during summer season
(Holmes et al. 2003)	Horse	Forelimb	the effects of perineural anesthesia on forelimb	High

2.11 Temperature and Its Relationship with Feed Efficiency

Feeding is one of the most significant factors in animal production. A high percentage of 90% of the cost is for feeding; it is important for institutions that are related to the animal industry to measure feed efficiency [104]. Residual feed intake (RFI) is the most popular method for measuring feed efficiency; RFI is predicting feed intake by an animal which is adjusted for weight gain. Negative values of RFI (low-RFI) mean higher efficiency than those with positive values (high RFI). RFI is time-consuming because it is needed to be applied for each animal individually. Compared to RFI, Infrared thermography is cheaper and a more useful tool for predicting the feed efficiency of the animal. (Martello et al. 2016) conducted a study about the correlation between body temperature and feed efficiency (RFI) of Bos indicus cattle in tropical conditions. Rectal temperature (RT), respiratory frequency (RF) and infrared thermography (IRT) were used to examine the front, eye, ocular area, and cheek, flank, ribs, rump and front feet. The results showed IRT high cattle with high feed efficiency (low-RFI), while IRT is low with cattle with low feed efficiency (high RFI).

Montanholi et al(2009) [105] pointed out that measuring temperature by using IRT for an eye, feet, and cheek are the most likely body regions for measuring feed efficiency in bulls. Results indicate that low temperature (IRT) in eye, cheek, and feet occurs with bulls with high feed efficiency (low-RFI). In a bull, the temperature is high with low feed efficiency (high RFI). Montanholi et al(2007) [106] stated that temperature of eyes for a steer with high feed efficiency (low and medium RFI) is less than for a steer with low feed efficiency (high RFI). In feeding behavior, the steer with high efficiency (low-RFI) consumes less food, eats slower and visits the feeder less often with the cool body (low temperature), high amount of baseline cortisol levels in comparison to a less efficient steer (high RFI). In this study, IRT measured eyes, cheek, snout, ribs and hind area [107]. Table 2.3 shows the feed efficiency in cattle and the relation with temperature.

Table 2. 3: Feed efficiency and correlation with temperature.

Author	**Animal**	**Body region**	**Feed efficiency**	**Temperature**
(Montanholi et al. 2007)	Steer	Eyes	High	Low
(Montanholi et al. 2009)	Bulls	eye, feet and cheek	High	Low
(Montanholi et al. 2010)	Steer	cheek, snout , ribs and hind area	High	Low
(Martello et al. 2016)	Bos indicus cattle	Front, eye, ocular area, and cheek, flank, ribs, rump and front feet.	High	High

2.12 Automated system for detecting stress

Many studies investigated developing automated non-invasive systems for detecting stress in animals in order to improve animal welfare and production. In 2016[108], research was conducted for developing an intelligent model for detecting stress in cattle using infrared thermography. Intelligent model developed was based on fuzzy logic, and fuzzy logic built on set temperature of different spot of cattle's body. These spots include eye, front, feet and flank of animal's body. Proposed fuzzy classifier has the ability to estimates the thermal stress level with average 85.4% accuracy. De Sousa et al (2018)[109] developed an automated model for prediction of thermal stress in feedlot finishing based on a non-invasive input dataset. In this study, an artificial neural network model was developed based on a group of thermal temperatures. The results showed that a neural network model has the ability to predict thermal stress with an average accuracy of 94.35%. Schaefer et al (2018)[110] conducted research about using infrared thermography with RFID to detect fever in cattle pre-slaughtering and the risk of producing dark-cutting. In this study, 2,263 cattle were tested with IRT with RFID. The results showed that the proposed non-invasive automated system has the ability to identify 60% of cattle with dark-cutting risk. Cattle with dark-cutting risk have higher temperature (35.8 ± 1.28 C) values or cooler (30.4 ± 1.85 C). Furthermore, cattle with fever (37.6 ± 0.53C) produce dark meat after slaughtering. It was suggested in this study that combining an infrared detection system with nutritional therapy treatment lead to detect and reduce by 50% dark-cutting in cattle. In 2019 [111], another attempt in the automation aspect was proposed for stress detection in pigs rather than cattle. In this study, a model was proposed based on Fuzzy logic to predict stress. Infrared skin temperature for 40 piglets was used to develop the fuzzy logic model. The results showed that the model has the ability to predict thirst (91%), hunger stress (67%), and the cold condition (46%) in pigs. The next section discusses and analyses the previous studies critically in order to identify our research direction.

2.13 Critical analysis

As mentioned in the section 2.12, many studies have investigated stress and its relationship with dark-cutting. In addition, studies emphasised invasive and non-invasive methods for detecting stress in different species by measuring HR, RR and body temperature. Invasive methods required the human to be physically close to the animal, which is not useful for large-scale implementation and it is costly as discussed in the section 2.7. Non-invasive methods using Infrared thermography have been used widely for diagnosing stress, inflammation and infection in different animals. For stress diagnosis, measuring eye temperature was used as an alternative method for body temperature[84]. Figure 2.2 shows the procedure for stress evaluation as used in previous studies. As shown in Figure 2.2, an infrared thermal camera captured the image and it is processed manually by experts in order to obtain eye temperature. Afterwards, captured temperature is used to detect stress and its impacts on animal production such as meat quality. However, recent studies from 2016 to 2019 investigated developing automated non-invasive systems for detecting stress using machine learning algorithms with infrared thermography as discussed in the section. The main limitation of these studies is lack of full automation as a result of ignoring using image processing and computer vision. For instance, automated localization for the eye region will lead to extract temperature automatically instead of manually. In addition, little research was done about stress detection with prediction of dark cutting. The author reaches this conclusion after checking well-known academic databases, which include science direct, IEEE, Scopus, web of science and google scholar with different keywords as mentioned previously in section 2.2. In this research, an automated system for detecting pre-slaughter stress in cattle is proposed with dark-cutting prediction. In this challenge, this study is using image processing and computer vision for face detection and eye segmentation. In addition, machine learning algorithms are used for stress assessment.

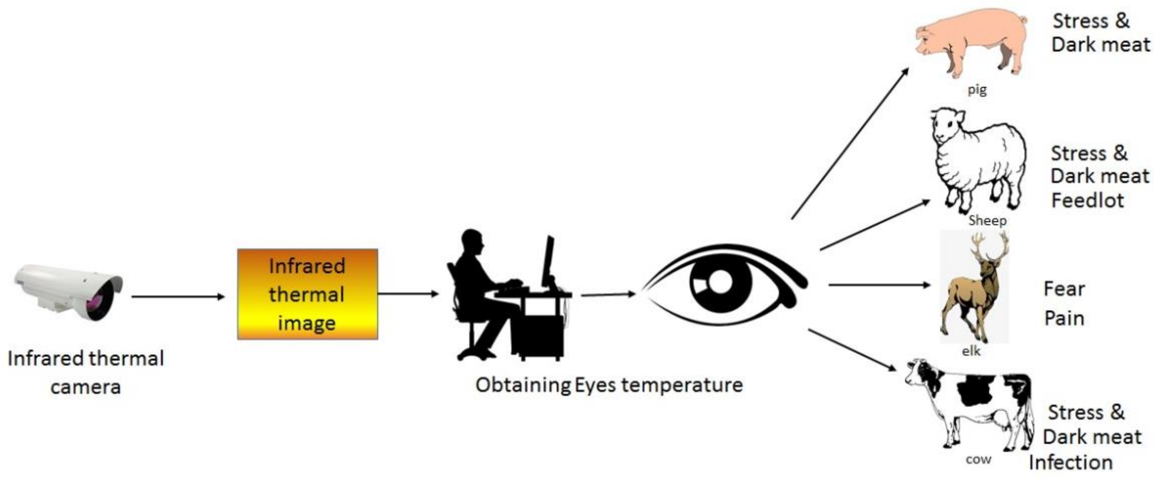


Figure 2. 2: Stress evaluation using infrared thermography

2.14 Conclusion

This chapter discussed an overview of the stress issue in cattle and its impacts on meat quality. This study is using Infrared thermal imaging for diagnosis of stress in cattle and animals and uses infrared thermal imaging for identifying illness and inflammation in cattle and animals. In addition, it discusses the negative effects of stress in feed efficiency in cattle. For all these aspects, the different number of studies are reviewed and analysed thoroughly. Therefore, even though there are several studies which investigate the role of infrared thermal in detecting stress in cattle, the automated system for detecting stress based on Infrared thermography has not yet been investigated thoroughly. The following chapter will illustrate more about the automated system that uses infrared thermography for medical diagnosis and its components in deeper details.

Chapter 3 Machine Learning, Computer Vision and Image Processing

3.1 Introduction

The aim of this study as mentioned in chapter one is developing an automated system for stress detection in cattle through using infrared thermal images. As explained in chapter two, the negative impacts of stress in cattle have been explained in detail and it has a negative role in animal production through producing dark meat. In addition, the role of IRT as a solution for stress issue in cattle is discussed.

In this chapter, the author reviews previous research and studies through gathering the research articles from different sources such as Web of Science, Science Direct, Scopus, IEEE and google scholar. Author concludes the following facts:

- There is no such automated system or method to detect stress in cattle using infrared thermal images. As illustrated in chapter two, all currently used methods are manual, and it is slow work through extracting temperature from the eye region manually.
- There is not any segmentation method used for eye segmentation in animals using infrared thermal images, and all current eye segmentation detection is applied on humans only.
- There is no any face detection method used for detecting the face region in animals, and all current face detection methods are applied on humans only.

As a result of these facts, this chapter reviews the state of the art in current systems and methods as well as inspects existing practices, problems, and prospects of image acquisition, pre-processing, segmentation, features extraction and classification about eye and face region in humans. All previous studies that were implemented in the visual spectrum image excluded and focused on infrared thermal only. Chapter start with the background section 3.2, which explain in detail the infrared thermography technique and its features. In the section 3.3, Computer Aid diagnosis systems the uses of infrared thermal images are illustrated, which represent automated systems that are used in medical diagnosis. In this chapter, we reviewed a

CAD system that close from our research area, which include CAD systems used in diagnosing fever, infection and stress. Afterwards, components of CAD systems are explained in detail. In section 3.4, pre-processing is elaborated on with its advantages. After processing stage, a comprehensive introduction about segmentation presented in section 3.5 with its methodologies and types, that explained in the subsections from section 3.5. Section 3.6 dedicated for automated segmentation, which includes eye segmentation as a subsection. The characteristics of thermal features that are extracted from the segmented or detected region are explained in section 3.7. Other methods for locating eye and face region based on object detection are reviewed in section 3.8. Machine learning which is considered as the last stage of CAD system is explained in section 3.9 with it is types and algorithms. Section 3.10 dedicated to the most used techniques in assessing the performance of machine learning methods. The CAD systems for diagnosing fever, infection and stress based on machine learning, image processing and computer vision introduced in section 3.12. The aim of this chapter is reviewing studies that are using infrared thermal for developing automatic diagnosis systems. Last section, researcher shows the general idea about proposed method with components and chapter summary in section 3.13 and section 3.14.

3.2 Infrared Thermography

Human beings are well-known as homeotherm, which mean the ability to keep inner body temperature stable regardless of the external influences that come from the surrounding cold or warm environment. Maintaining the stability of inner body temperature is a result of the thermoregulatory mechanism of the human body. This thermoregulatory mechanism in the human body includes autonomic nervous reactions and behavioural changing towards the variations in temperature from the surrounding atmosphere. Autonomic nervous reactions in the human body involve cutaneous vasomotor and sweating due to decrease heat. Consequently, abnormal changing in human body temperature could be a sign of disease or inflammation[112-114].

Historical background behind using thermography in diagnosis commenced from an ancient Greek civilization around 480 BC. According to the ancient writing of Greek physician Hippocrates, colour changing during drying of mud placed on a particular part of the patient body can be used as an indicator of disease in that body part[115]. This phenomenon is developed throughout history, which leads to producing many physical achievements. In 1800, William Herschel discovered the acquisition of thermal radiation from the human body[116]. Based on physics science, every object including human body with a temperature higher than absolute zero has the ability to emit electromagnetic radiation, called infrared radiation[117]. In addition, human skin has amount of emissivity in wavelength range 2–20 µm and an average peak of 9–10 µm. In 1934[118], was the first study to explore the physiological characteristics of radiation heat emitted from the skin surface. This study stated that changing physiological activities can be tested by using skin thermal properties as a result of changing in skin temperature. This means temperature of skin using infrared measurement can be employed for diagnostic purposes. Based on this fundamental idea, infrared thermography was presented as a new imaging method to medical science. In the decade that followed in 1956 [119], Lawson was the first scientist who presented infrared thermography for breast cancer diagnosis through measuring skin temperature. Afterwards, infrared thermography was suggested as a new tool for breast lesions study.

The temperature that is emitted from an object can be shown as a 2D image, and this can be accomplished by using Infrared Radiation (IR). IR spectrum light has different wavelength that can be classify into three categories[120]:

- Near IR: it is close to visible light with wavelengths ranging from 0.7 to 1.3 microns.
- Mid IR: it has wavelength in range 1.3 to 3 microns.
- Thermal IR has wavelength in range 3 to 30 microns.

Nowadays, Infrared Radiation Thermography (IRT) is used widely to show temperature distribution of an object as a thermogram image. Unlike other objects, the black object has different characteristics regarding radiation and temperature. The black object has the ability to receive all radiation energy that reaches it without reflecting anything back[121, 122]. Spectral intensity I of thermal radiation of black object at temperature T at all wavelength λ can be computed through following equation (3.1):

$$I_{\lambda,b}\,(\lambda,T) = \frac{2\pi hc^{-2}}{\lambda^5(e^{\frac{hc}{\lambda kt}} - 1)}\; W\,cm^{-2}\mu m^{-1} \tag{3.1}$$

h refer to the Planck constant ($6.626 \times 10^{-34}\,J\,S$), K means Boltzmann constant($1.381 \times 10^{-32}\,J\,k^{-1}$), c is the speed of light in vacuum($2.998 \times 10^{8}\,m\,S^{-1}$), λ means wavelength and T refers to absolute temperature.

After using Planck function and Stefan-Boltzmann's law, overall emissivity of a black object is defined as follow[123]:

$$E_b = \int_0^{\infty} \frac{A_1}{\lambda^5 (e^{\frac{A_2}{\lambda T}} - 1)} d\lambda = \sigma T^4 \tag{3.2}$$

where σ means the Stefan-Boltzmann constant ($5.67 \times 10^{-8}\ w/m^2\ k^4$). Based on the Stefan-Boltzmann's law and after calculating the ratio emissivity of radiation of real object to black object at the same temperature, emissivity for real object can be computed as follow:

$$E = \varepsilon \sigma T^4 \tag{3.3}$$

where ε represent the emissivity of the surface at fixed wavelength and absolute temperature T. The table shows the emissivity of human skin [124].

Table 3. 1: The emissivity of human skin [124]

Tissue	Emissivity
Black skin (3–12 μm)	0.98 ± 0.01
White skin (3–14 μm)	0.97 ± 0.02
Burnt skin (3–14 μm)	0.97 ± 0.02
Epicardium (fresh: 0.5 h) 3 μm	0.85
Epicardium (fresh: 0.5 h) 5 μm	0.86
Epicardium (9 days at −20 °C)	0.99
Pericardium (3 μm)	0.88
Pericardium (5 μm)	0.94
Pericardium (9 μm)	0.95

According to [125], the emissivity of animal skin is 0.95 for cows, bovine,pig and ewe sheep. Emisivity is one of the signficant factors , which need to be considered during use of an infrared thermal camera.

Several distinct features of infrared thermography make it the best choice for many researchers. IRT is a fast method that visualizes temperature as an image in real time without influencing local temperature. Also, it is a non-invasive, non-contact approach and 100% side- effect free. Therefore, the clinical public in the US presented infrared thermography as a medical imaging tool that can be used for diagnostics purposes. After decades of using the infrared thermal camera, many studies confirm that some criteria required considering in order to obtain accurate diagnostic. These criteria include preparing the patient, environmental factors such as atmospheric temperature and acquisition standardization of infrared thermal camera. Through considering these factors and advancement in quality of infrared thermal camera, many Computer-Aided Diagnosis (CAD) processes were proposed to diagnose different diseases such as: fever, diabetes, breast cancer, dry eye and skin cancer[126, 127].

3.3 Computer-Aided Diagnosis system

CAD has an important role in analysing and obtaining important information from IR images. Manual examination IR by a human is often unsophisticated as a result of many errors. These errors are occurred due to human nature such as fatigue, being lazy, and manual processing for a huge amount of information. Also, inaccurate diagnosis has occurred due to humans having limited visual perception. For instance, optical illusions have a negative impact on diagnosis accuracy. In addition, there is a lack of qualified IR examiners. These facts lead to developing a CAD system, which has the ability to analyse the IR image automatically to diagnoses disease. Current research emphasis is on enhancing the accuracy of IR image processing through developing methods for segmentation, image enhancement and restoration, feature extraction and classification[127].

The general structure of the CAD system is shown in Fig.2. Mainly, CAD systems can be classified as: offline and online systems. In the offline system, input infrared thermal image is pre-processing through applying different techniques involving enhancement, removing noise and Area of interest (ROI) by applying segmentation. Afterwards, feature extraction methods are applied to obtain important features from ROI. Extracted features are then used in the subsequent classification stage. In classification stage, extracted features are divided into a number of classes with ground truth being used to train the classifier. However, in online systems the same significant features are obtained from ROI and then features are classified to particular class. Each stage of CAD system will be explained in detail in the next sections.

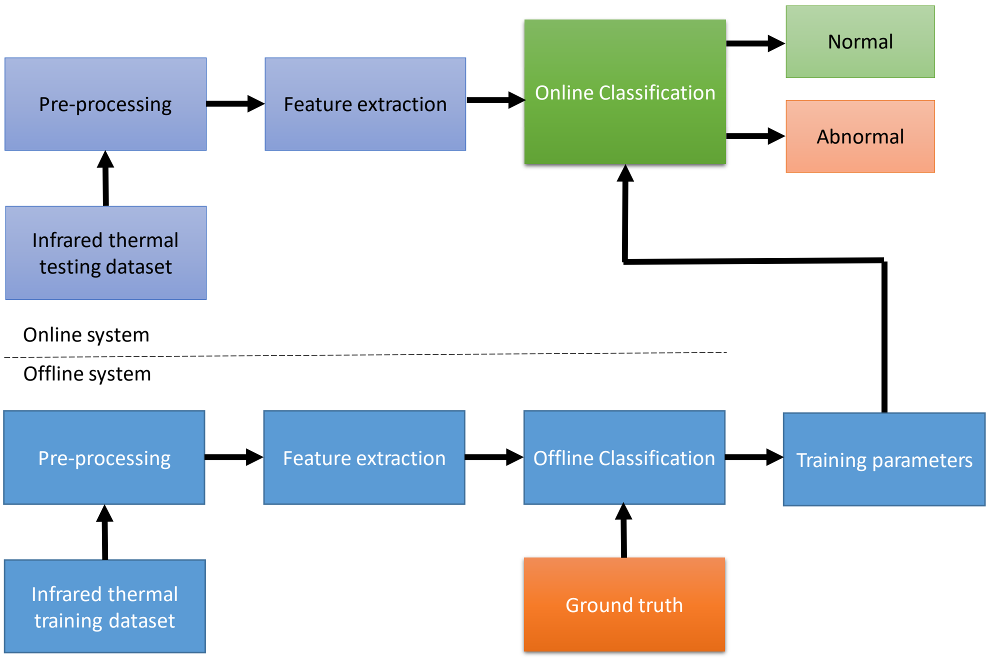


Figure 3. 1: General components of CAD system.

3.4 Pre-processing

The infrared image could be captured with inconsistency in term of intensity as result of an external source of light such as sunlight and bulb. Thus, there is a need to do resizing of the image through using techniques such as template and interpolation methods [128]. Another source of inconsistency is changing in light conditions or the light noise that comes from Infrared image capturing techniques. Histogram equalization can be used to remove irregular background that could lead to undesirable lighting in Infrared image [129]. This method could enhance pixel intensity values for further processing in subsequent processes.

3.5 Segmentation

Image processing has a significant role in transforming data from image to useful information. It is used widely for removing noise, image enhancement and ROI extraction. Besides, segmentation is another image processing technique that is used as an initial step in image processing and computer vision. Two goals can be reached from using segmentation. Firstly, dividing an image into a number of regions and using important region for further analysis. Second goal is changing the form of image for faster analysis[130].

In medical IRT, disease and inflammation can identified visually by human. Human based diagnoses are not preferred as a result of several factors such as, error, oversights, exhaustion workload and eye fatigue from long-time visual monitoring. Also, many diseases require statistical analysis for ROI. In addition, human body organs and parts have different geometrical forms, which leads to include background data in capturing ROI manually[131]. Thus, segmentation of ROI is necessary for thermographic analysis.

ROI segmentation can be classified as manual, semi-automatic and fully automatic segmentation. ROI segmentation in manual approach is identifying boundaries of ROI by using particular software. Semi-automatic refers to automatic segmentation that is only achieved with human intervention. Human intervention is required for decreasing search region until reach to segment ROI entirely[132].

Segmentation for ROI can be obtained by Thresholding, Edge detection, Region growing and Feature based clustering[133, 134]. Advance image processing methods such as convolutional neural networks (CNN) and deep learning performs well in thermal image segmentation[132].

3.5.1 Thresholding Segmentation

Thresholding segmentation refers to identifying the borders of the desired object from background through converting grey scale image which is input to binary output. This segmentation method applies a single value for all pixels in an image. This single value is called the threshold value. The advantage of obtaining binary image from grey scale image is reducing data complexity and using binary output for recognition and classification[135]. After applying threshold value, Binary output is defined as follows:

$$g(x,y) = \begin{cases} 1, f(x,y) > T \\ 0, f(x,y) < T \end{cases} \tag{3.4}$$

where $f(x,y)$ refers to pixel location of image in grey scale form and T means threshold value. $g(x,y)$ means binary image that contain ROI region with 1 labelling and 0 for background region[135].

Based on selection threshold value, there are two type of thresholding methods: global and local thresholding. Global thresholding means identifying threshold value manually or constantly, but approaching threshold value automatically is called local thresholding[136].

3.5.2 Edge based Segmentation

This segmentation is based on extraction edges and boundaries from an image. Edges and boundaries are used as features for further processing until the object can be distinguished from the background. There are various types of edge detection segmentation methods. The most popular used are Sobel, Roberts, Prewitt, Laplacian of Gaussian (LoG) and Canny, that are briefly discussed in the next subsections[133].

3.5.2.1 Sobel

The Sobel edge detection is calculation of the gradient through applying discrete difference between rows and columns with size 3x3 neighbourhood. As shown in Table 3.2, applying below mask in two direction, horizontal and vertical, leads to identify edges and boundaries of image[137].

Table 3. 2: Sobel mask.

+1	+2	+1
0	0	0
-1	-2	-1

G_X

-1	0	+1
-2	0	+2
-1	0	+1

G_Y

3.5.2.2 Roberts

This edge detection method is processing image pixels in horizontal and vertical direction in order to compute edges. Afterwards, edges in horizontal and vertical are combined together. This operation is achieved through applying 2D mask as showing in Table 3.3 below[138]:

Table 3. 3: Roberts mask.

+1	+2
0	0

G_X

-1	0
-2	0

G_Y

3.5.2.3 Prewitt

Edge detection using Prewitt is estimating the magnitude and orientation for a particular edge. Prewitt is well known in the image processing field as the best edge detector. Edge detection can be achieved through using following mask as shown in Table 3.4 below[139]:

Table 3. 4: Prewitt mask.

-1	-1	-1
0	0	0
-1	-2	-1

G_X

-1	0	-1
-2	0	+2
-1	0	+1

G_Y

3.5.2.4 Laplacian of Gaussian

Edge detection by using Laplacian of Gaussian can be obtained through searching for zero in the second derivative of the image. This method is used to find whether a pixel is in the dark or light side of the edge[140].

3.5.2.5 Canny

The Canny edge detection includes several stages until edges are identified. It has the ability to detect a wide range of edges in an image. Edges can be detected by applying local maximum of the gradient, and gradient can be obtained through using the derivative of a Gaussian filter[137].

3.5.3 Region-based Segmentation

Region-based segmentation divides image into several regions and applies statistics among regions to segment a particular region. Region is set of pixels that have similar properties, which is called a homogeneous region. Segmented region could belong to a particular object or part of an object. This kind of segmentation method performs well in noisy images[134].

3.5.4 Clustering-based Segmentation

Clustering is the procedure of categorizing objects in an image based on similarity in some properties. Based on this fundamental, objects in image are classified into a number of clusters, and according to similarity and dissimilarity in properties, each cluster contains some objects that are different from objects of other clusters. Many algorithms have been developed to find clustering. Image clustering required to know how to represent an image, and how to organize image, and also, how to classify the image to a particular cluster. Most well-known clustering methods are K-mean clustering and Fuzzy C- Means (FCM)[134].

K-means clustering has the ability to solve the clustering problem in a robust and fast way. Also, it is an unsupervised approach. It can classify the dataset to a number of clusters and this number is identified prior. It is able to classify an image to a number of clusters accurately when datasets are dissimilar. Fuzzy clustering is an approach that allows objects to be assigned to more than cluster with different membership. This method can perform effectively in pattern recognition. Most well-known used algorithm is Fuzzy C-Mean. In FCM, many clusters are organized based on assigning different membership to each cluster[141]. Summary of segmentation methods is shown in Table 3.5 below.

Table 3. 5: Summery of general categorization of image segmentation methods [134].

Parameter	Thresholding Segmentation	Region based Segmentation	Edge based Segmentation	Cluster based Segmentation	Fuzzy C-means Segmentation
Spatial information	Ignored	Considered	Ignored	Considered	Considered
Region continuity	Reasonable	Good	Reasonable	Reasonable	Good
Speed	Fast	Slow	Moderate	Fast	Moderate
Computation Complexity	Less	Rapid	Moderate	Rapid	Moderate
Automaticity	Semiauto	Semiauto	Interactive	Automatic	Automatic
Noise Resistance	Less	Less	Less	Moderate	Moderate
Multiple Object Detection	Poor	Fair	Poor	Fair	Fair
Accuracy	Moderate	Fine	Moderate	Moderate	Moderate

3.6 Automatic segmentation in Infrared thermography

Infrared thermal image is temperature distribution with variant colour, which is different from visual spectrum images. Also, it has a dynamical colour and features. Automatic segmentation of ROI is very challenging compared to the visual spectrum as a result of changing in thermal patterns and colour distributions. Image with the visual spectrum can be used as supportive feature with the thermal image in order to enhance segmentation of anatomical parts of the human body [142-144]. In addition, many studies stated that using external markers leads to improve ROI identification. Also, using external markers affects temperature distribution in ROI. Moreover, many research studies produced various software solutions, which can be used for automatic segmentation. As shown in Figure 3.2, automatic segmentation for ROI can be classified into segmentation for full region, segmentation for organ region, segmentation for diseased region. Full region segmentation involves edge detection and thresholding, which is used to segment a specific body region from background. Anatomical region segmentation includes the anthropometric, geometrical and local thermal characteristics and is used to segment the particular anatomic region from the human body. Last segmentation type is segmenting diseased region. In this category, the Fuzzy c-means, k-means and region-growing algorithms are used to segment the warmest or coldest areas from the human body [132].

In the medical sector, many studies have developed different automatic segmentation methods to locate several regions of the human body. Summary of automatic segmentation methods of different ROI that are used in medical IRT with their methodologies and statistical performance is illustrated through Table 3.6.

In order to evaluate segmentation performance, statistical comparison is conducted between extracting ROI using automatic segmentation with obtaining ROI with ground truth (GT). Generally, many evaluation methods are proposed for measuring how segmentation method is correct in obtaining ROI; these methods include Hausdorff distance (HD), region overlap measures, Jaccard index, sensitivity, specificity, F-score, misclassification and Youden index[145-147].

So far, there is no particular method that is agreed upon by all researchers, that is used as a standard to evaluate the performance for segmentation method compared to GT.

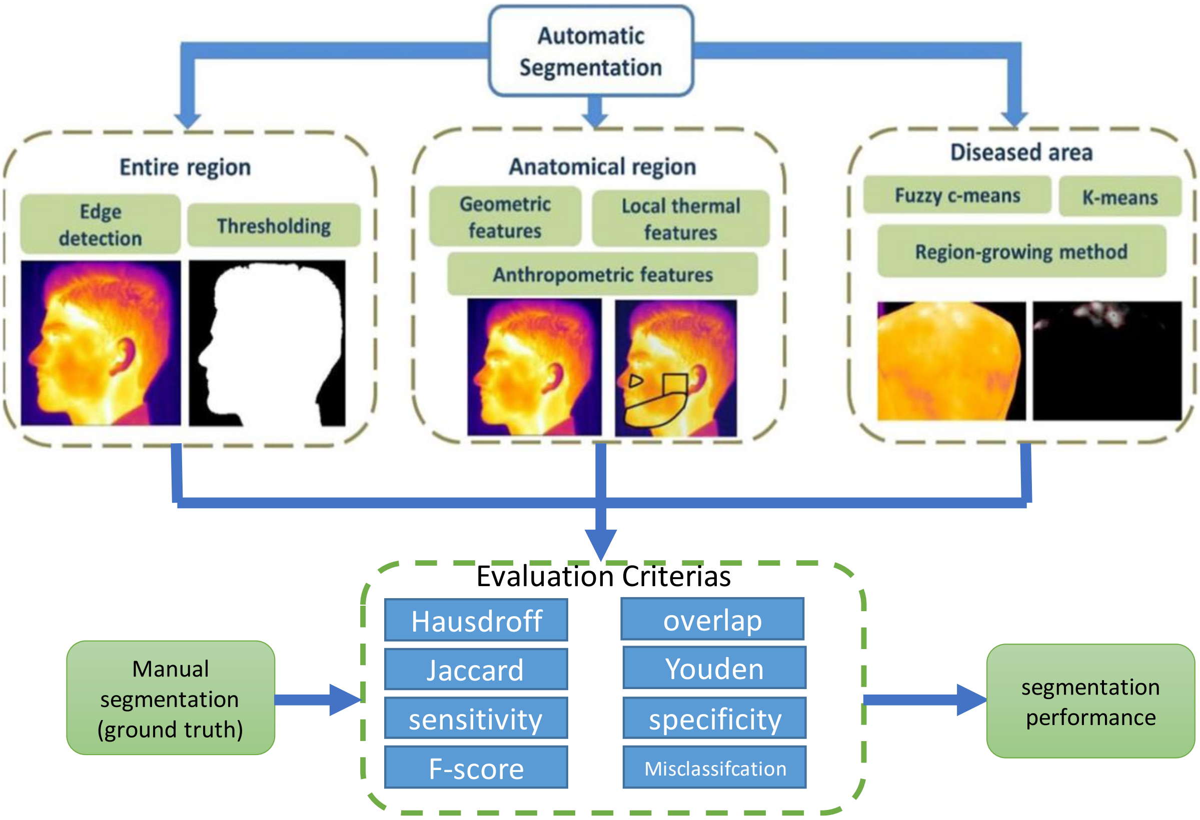


Figure 3. 2: General catgorization for automatic segmentation methods[132]

Table 3. 6: Summery of automatic segmentation methods used in medical IRT[132].

ROI	Target	Segmented region	Methodology	Evaluation metrics
Breast	Benign tumour • Malignant tumour • Lymphatic congestion	Frontal breast • Inframammary fold • Axilla • Medial border	• Canny edge detection • Gradient operator • Hough transform • Polynomial curve fitting • Thresholding and mathematical morphology • Anisotropic diffusion filter and level set method • Topological derivative • Gradient vector flow snake method • Random Walkers method • Directional SUSAN edge detection	Jaccard Index • Dice and Volume similarity • Hausdorff distance • Youden index • Other overlap Measures
		• Diseased area	• Clustering algorithms • Extended Hidden Markov Model • Parametric active contour model	• Hausdorff distance

			• Hybrid intelligent technique	
		• Nipple	• Abridged rule-based method • Anatomical and visual features of nipple	•Recall • precision • F-score
		• Lateral breast	• Histogram-based thresholding, mathematical morphology and Shi-Tomasi method	•Not specific
Face	•Paranasal Sinusitis • fever detection	Frontal View • Forehead • Eyes • Nose • Mouth • Frontal sinus • Maxillary sinus	• Geometrical features and local thermal patterns • Anthropometric ratios • Harris operator and k-means clustering • Haar wavelet and Gentle Boost algorithm	• Displacement error • Overlap measures
	• Chronic orofacial pain • Inferior alveolar nerve deficit •Temporomandibular joint disorder • Myofascial trigger points	Lateral View • Mandible •Temporomandibular joint	• Geometrical features and local thermal patterns	Euclidean distance
Eyes	• Dry eye • Central retinal vein occlusion • Exophthalmos • Glaucoma • Uveitis • Keratitis	• Ocular region • Cornea	• Genetic and Snake algorithm • Genetic algorithm, snake algorithm, Gabor filtering and expectation-maximization algorithm	• Not evaluated
	• fever detecting	• Inner canthus of Eye	• Morphological operations, geometric features and cross-correlation • Structural information and temperature distribution characteristics of face	• Displacement error
Foot	•Diabetes mellitus •Neuropathic ulceration	• Plantar region • Ulcerous region	• Visual imaging, unsupervised learning algorithm-based segmentation and non-rigid landmark-based registration	• Overlap measures and

			• Edge detection and water shed technique • Snakes algorithm and fuzzy c-means clustering • Genetic algorithm and geometric transformation • Scalable scanning technique based on genetic algorithm • Obstructive IR device and histogram-based thresholding • Active contour without edges and non-rigid registration • Active contour and iterative closest point based rigid registration	mean distance error
		Plantar angiosomes • Medial plantar artery • Lateral plantar artery • Medial calcaneal artery • Lateral calcaneal Artery • Toes • Forefoot regions • Rear foot regions	• Visual image-based thresholding, Hough transform and region-growing method	• Not specified
Hand	• Carpal tunnel syndrome • Raynaud's syndrome • Rheumatoid arthritis • Tenosynovitis	• Dorsal region • Palmar region • Fingertips • Palm and palm regions	• Otsu's thresholding and morphological operations • Level set and genetic algorithm • Visual imaging, Otsu's thresholding and simplex search method • Mean grey-level intensity- based thresholding, Hough transform and region-growing method • Modified Otsu's thresholding and morphological operations	• Modified Hausdorff distance

		• Fingertips • Phalanges	• Fixed value (0.2) thresholding, Hough transform and geometric information	• Mean temperature difference
		• Diseased area	• Expectation maximization and fuzzy c-means algorithm • Fuzzy c-means and k-means algorithm • K-means algorithm	• Not evaluated
Limbs	• Arthritis • Injury • Stress fracture	• Silhouette • Diseased area	• Modified Otsu's thresholding and region-growing method • Sobel edge detection and region-growing method • Discrete wavelet transforms	• Not evaluated
		• Shin regions	• Mean grey-level intensity- based thresholding, offsets and region-growing method	• Not specified
	• Knee osteoarthritis • Medial collateral ligament injury • Bursitis	• Knee Patella •Sub-regions surrounding the patella	• Segmentation based on patella-centering	• Not evaluated
Trunk	• Faulty posture	• Neck • Shoulders • Arms • Hips	• Otsu's method and geometric features	• Not evaluated

3.6.1 Eye Segmentation

Many algorithms have been proposed for eye segmentation and use of segmented region in disease identification and analysis. Temperature measurement of eye region leads to identify disease such as ocular diseases or to obtain body temperature. For these purposes, many researchers investigate developing Semi-automated and fully automated eye segmentation. In this section, we review different methods used for eye segmentation. Some methods used thresholding with temperature and other methods used classifiers with features such as HOG, LBP and Haar. Summary of these methods is shown in Table 3.7. Next subsection illustrates a recently used method with its methodologies and results.

Table 3. 7: Summery of eye segmentation methods used in medical IRT.

Year	Methodology	Evaluation Metrics
(Tan, Ng et al. 2008, Tan, Ng et al. 2009)	- Use snake algorithm to find contour and use this contour to localize eye and corneal region.	- Not evaluated
(Wang, Shen et al. 2012)	- Projection curve for identify face with eyeglasses. - Haar features used with SVM to create 8 classifiers, and use these classifiers for eye detection in frontal position.	- Accuracy:75% in Equinox database - Accuracy: 88% in NVIE database.
(Wang, Shen et al. 2012)	- Temperature normalization used to identify foreground. - Randomize Hough Transform used to find face. - Template-matching, knowledge-based and morphological methods used to locate eye region. - Temperature difference used to find inner canthus	- Accuracy:97%
(Marzec, Lamża et al. 2016)	- Brightness distribution of eye region used as features to train neural network.	- Displacement error: - Detection rate:
(Budzan and Wyżgolik 2013) (Marzec, Lamża et al. 2016)	- Using HOG features with SVM. - 500 image for training and other 500 for testing.	- Sensitivity:92% - Specificity: 98% - F-Measure:95%
	- Using Haar features with cascade classifier. - 500 image for training and other 500 for testing.	- Sensitivity:83% - Specificity: 90% - F-Measure:86%
	- Using LBP features with cascade classifier. - 500 image for training and other 500 for testing.	- Sensitivity:87% - Specificity: 89% - F-Measure:88%
	- Temperature threshold 34 and area threshold used to segment face. - Used high intensity for upper face to localize inner canthus	- Accuracy eye detection :80% - Accuracy inner canthus:100%

3.6.1.1 Eye localization based on Haar features and projection curve

This combination between projection curve in binary image and Haar-like features has shown success in eye localization. This algorithm starts with extracting human body from binary image using thresholding via Otus method. After converting grey image to binary, face region is detected using horizontal and vertical projections. Then, face region in grey form is divided into 15 sub-regions. Haar features are extracted from these sub-regions and AdaBoost algorithm is used for selecting features that relate to the eye region. Afterwards, eight classifiers are trained on extracted Haar features by using SVM algorithm. Voting strategy is used to identify eye region. This proposed algorithm has been tested on two databases Equinox and NVIE database seeking evaluation. Based on displacement error measurement, it is accurate with percentage 75% in Equinox and 88% in NVIE database[148].

3.6.1.2 Eye localization based on brightness features

Fast eye localization proposed is based on brightness distribution of eye region. Brightness distribution between two eyes is used as features to train neural network. The authors stated that this proposed method is robust for eye localization in different situations such as position, scale, and orientation of face region. In order to assess localization performance, the displacement error is used to compare between proposed method result and ground truth. Also, detection rate use to evaluate proposed method. Consequently, the authors stated the effectiveness of the proposed method with percentage 91% of localization accuracy and fast localization with approximately 0.06 s per thermal image[149].

3.6.1.3 Eye localization based on geometrical features

Budzan et al. [150] used geometrical features to locate face and after that eye region. In this method, infrared thermal image for human normalized based on temperature difference is used to remove background and identify human body. To detect face region, Randomized Hough Transform is used to locate ellipse shape used in this algorithm to find face under the assumption that the human face looks like an ellipse shape. Then, the template-matching, knowledge-based and morphological methods are used to locate the eye region. Afterwards, segmentation for homogeneous region with temperature difference is used to locate the inner canthus of the eyes. This algorithm has shown 97.1% in term of accuracy when subject is placed 1.5 m from the infrared thermal camera.

3.6.1.4 Eye localization based on Active contour model algorithm

Tan et al. [151, 152] presented an automatic method for eye segmentation through employing the snake algorithm with target tracing function to localize the eye and cornea region, and using genetic algorithm to locate the initial contour and provide it to the snake algorithm. Afterwards, location and boundaries of cornea are detected by using snake points. According to results, proposed method succeeds with percentage 90%. This proposed method is enhanced by same authors through removing eyelashes. Eyelashes can be eliminated by involving three stages. Firstly, using normalization after eye localization. Second stage is using Gabor filtering, and expectation-maximization algorithm as the third stage. Authors pointed out that this modification leads to a significant enhancement compared to the previous approach.

Active contour model (snake) is considered an important model that is used in segmentation and localization for region of interest [153]. Snake functions involve finding contours like lines and edges, tracking contours during motion and matching them in stereopsis. The conceptual idea behind Snake algorithm is formulated curve by reducing energy spline that follows internal spline energy, image force and external constraint force. Due to it slithering to target contour as a result of minimizing energy, it is called snake. When an expert user puts the snake close to a desired contour, minimization of energy will be applied on the image. Image force pushes the snake towards the desired contour such as edge and line. External constraint force is responsible for pushing the snake near to the desired local minimum energy. These forces come from user input, automatic attentional mechanisms or high level of interpretation. The contour points of curve that should be close to objects boundary is x(s) = [x(s) y(s)], s $\in$ [0,1]. Snake algorithm will move contours around object by using external and internal energy as shown in the following equations:

$$E = \int E_{int}(X(s) + E_{ext}(X(s))ds \qquad (3.5)$$

$$E = \int_0^1 \frac{1}{2}\left[\alpha|X'(s)|^2 + \beta|X''(s)|^2\right] + E_{ext}(X(s))ds \qquad (3.6)$$

In equation (3.6), α and β parameters are used to control the length and strength of snake. The external energy for (x,y) in grey level involves:

$$E_{ext}(x,y) = -|\nabla I(x,y)|^2 \tag{3.6}$$

$$E_{ext}(x,y) = -|\nabla G_{\sigma}(x,y) \times I(x,y)|^2 \tag{3.7}$$

As shown in equations, ∇ represents the gradient operator, G_{σ} refers to the 2D Gaussian function, and σ is standard deviation. And the numerical solution for (Equation (3.6)) include:

$$\{x_t = (A + \gamma I)^{-1}(\gamma x_{t-1} - f_x(x_{t-1}, y_{t-1}))$$

$$\{y_t = (A + \gamma I)^{-1}\left(\gamma y_{t-1} - f_y(x_{t-1}, y_{t-1})\right)$$

A means pentadiagonal banded matrix, γ is step size and $\nabla E_{ext} = [f_x(x,y)\ \ f_y(x,y)]$.

Two issues are noticed after implementation of snake algorithm [154]. First issue is initial contours of snake must be near to the region of interest in order to segment it accurately from image. When initial contour is not near to the region of interest, this leads to a wrong result. The second issue of snake algorithm is difficulties in processing the boundary concavities. (Xu & Prince 1998) [154] improved snake algorithm by solving these issues by using new external energy called gradient vector flow (GVF). GVF are thick vector fields derived by reducing energy based on region of interest. Vector can be assumed as v(x,y) = [u(x,y),v(x,y)] is gradient vector flow field that reduce the energy functions.

$$\varepsilon = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f_e|^2\, |v - \nabla f_e|^2 dxdy$$

In this equation, μ is the parameter that is computed by the first term and second term of integrand, and this parameter should be higher if there is a high amount of noise in the image; $f_e(x,y)$ refers to edge map Equation(7)).

$$f_e(x,y) = -E_{ext}^{(i)}(x,y) \tag{3.8}$$

where i = 1, 2 corresponding to equation (3.6), (3.7) appropriately.

$$\begin{cases} u_{i,j}^{n+1} = \left(1 - b_{i,j}\Delta t\right)u_{i,j}^{n} + r\left(u_{i+1,j}^{n} + u_{i,j+1}^{n} + u_{i-1,j}^{n} + u_{i,j-1}^{n} - 4u_{i,j}^{n}\right) + c_{i,j}^{1}\Delta t \\ v_{i,j}^{n+1} = \left(1 - b_{i,j}\Delta t\right)v_{i,j}^{n} + r\left(v_{i+1,j}^{n} + v_{i,j+1}^{n} + v_{i-1,j}^{n} + v_{i,j-1}^{n} - vu_{i,j}^{n}\right) + c_{i,j}^{2}\Delta t \end{cases}$$

where $b(x,y) = f_{e_x}(x,y)^2 + f_{e_x}(x,y)^{2\prime}$

$c^1(x,y) = b(x,y)f_{e_x}(x,y)$

$c^2(x,y) = b(x,y)f_{e_y}(x,y)\ ,\ r = \frac{\mu\Delta t}{\Delta x\Delta y}\ ,$

3.6.2 Inner canthus segmentation

Inner canthus of eye region has the highest temperature compared to other parts of the face [155].For this reason, inner canthi of the eyes are well-known as the most constant regions that are used extensively in measuring human body temperature and are applied for fever detection. Based on this fact, many algorithms have been proposed for locating this distinct region. Eye corners can be located through applying the local maxima and high gradient in the face region. Face region can be extracted through applying Otus thresholding [156]. Another suggested method is using temperature thresholding or high intensity to locate inner canthus[157]. In this method, it is required to minimize the search region by locating the face region first through applying temperature threshold with selecting known area blob. After segmenting face region, eye region is identified by selecting the area in the upper face.

3.7 Thermal Features and Statistical Analysis

Segmentation in the medical field aims to identify important regions from the human body. As a further step, thermal features and statistical parameters are extracted from the segmented region. Extracted features are used later on for classification (or diagnosis) particular of illness and this process is known as thermographic analysis. Generally, the histogram-based first order parameters, like mean temperature, standard deviation, kurtosis, skewness, entropy etc. are employed to define the thermal asymmetry[117, 158].

In thermal tomography, advanced methods can be used such as Fast Fourier and Wavelet transform to conduct analysis in sequential thermal[158, 159]. An enormous number of features can be extracted from an ROI and for this reason optimized ensemble of features is essential for an effective diagnosis. For this reason, the linear and nonlinear transformations, like principal component analysis (PCA), generalized discriminant analysis (GDA) and linear discriminant analysis (LDA) are applied.

Generally, the classification is completed based on the extracted features. These features can be formalized by using simple threshold values for these features. Another way is feeding features to the modern classifiers[117]. For classification, the artificial neural network (ANN), support vector machine (SVM) and fuzzy logic are used extensively for automatic diagnosis.

3.8 Computer Vision

Object localization is part of computer vision. Computer vision is image understanding in a disciplined way that interprets, recognizes, and reconstructs objects of a captured image. Computer vision has been applied widely in different areas such as optical character recognition, machine inspection, object recognition, 3d model building, medical imaging, automotive safety, match move, motion capture, surveillance, fingerprint recognition and biometrics, stitching, exposure bracketing,morphing,3D modelling, video match move and stabilization, photo-based walkthroughs, face detection and visual authentication.[160]. Computer vision system has several components as demonstrated in figure 3.3 [161].

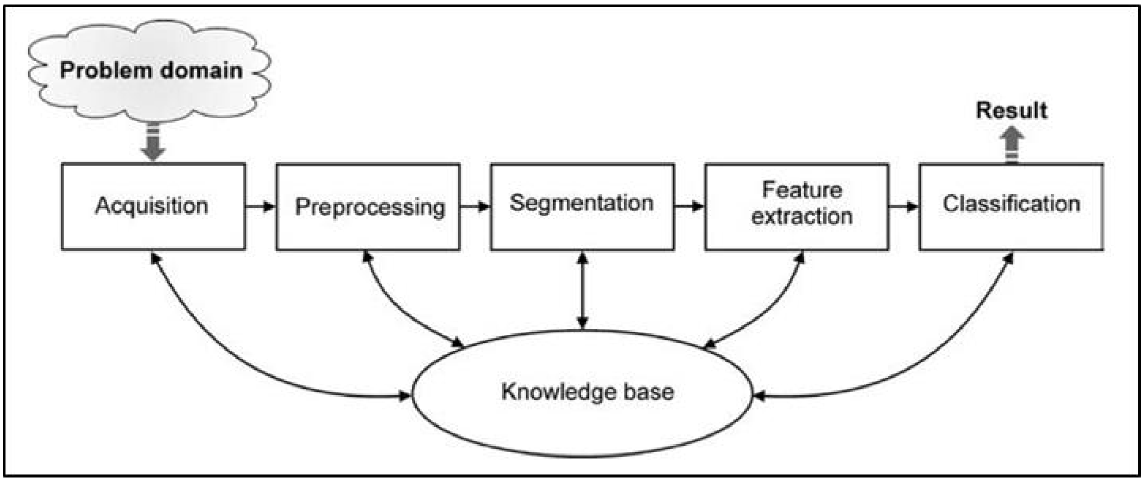


Figure 3. 3: Diagram of a computer vision system [161]

As shown in Figure 3.3 above, any problem domain follows a sequence of processes until obtaining results. For example, a problem domain that needs to be solved is automatically recognizing license plates at highway toll booths. In this case, the goal is the ability to extract alphanumeric contents of the license plate of a vehicle in an automated and unsupervised method.

The procedure to solve this problem contains five blocks: acquisition, pre-processing, segmentation, feature extraction and classification. Acquisition block refers to acquiring image through using camera; acquired image is involving vehicle with clear licence plate. Captured image should be in good lighting and resolution that is appropriate for further processing. This block represents the input device for the next block. In pre-processing block, image gets enhancement by employing some algorithms for removing noise, contrast improvement and brightness correction. The goal of this part is to increase the quality of the captured image by showing clear characters of the license plate. The segmentation block is responsible for dividing an image into foreground object and background, and for keeping only objects or areas of interest. For example, number plate recognition includes extracting the license plate from the rest of the original image, and segmenting characters within the plate area. Automatic segmentation is one of the most challenging tasks in a computer vision system. The feature extraction is responsible to analyse the image's content in a descriptive way. Features involve color (or intensity) distribution, texture, and shape of the segmented region. Extracted features are categorized into group of feature vector that will be used as input for classification stage. In case of problem domain, character features is encoded to feature vector to use after that in classification. In classification stage, feature vector will be used to input by using different classification techniques such as neural network; it will be able to label character and producing string (or ASCII file) that contains the content of the licence plate. Knowledge base is representing the amount of data that is used in all processes of computer vision system to produce accurate results. In the next section, many face and eye localizations methods are reviewed with their methodologies and findings.

3.8.1 Face Detection using Infrared Thermography

Face detection has been used widely in thermal imaging as a result of several advantages of thermal imaging compared to conventional visual spectrum imaging. Unlike the visual spectrum, thermal imaging has constant illumination and for this reason, many studies used face detection in a thermal camera for surveillance purposes[162-164]. Moreover, physiological readings such as respiratory and heart rate (RR/HR) are obtained from the face region via thermal imaging [165]. In addition, many studies focused on using infrared thermal imaging in emotion and stress detection as well as polygraph analysis [166, 167].

All of these applications of using infrared thermal imaging require identifying the face region first as ROI through applying a face detection algorithm. Face is identified as ROI manually or automatically by using face detection algorithm. In most studies in literature, identification for face region must be in frontal view. Most well-known used method in literature was the Haar-based Viola-Jones face detection algorithm[168].

On the other hand, there is a lack of literature in developing a face detection algorithm and using it in the infrared thermal images, while a massive number of studies proposed many face detection algorithms for a visual spectrum image. The reason for this lack is all current methods are based on machine learning, which includes features extraction and automatic classification. Face detection based on machine learning requires manual annotation for the face region of a massive number of images. This number of images is not available for infrared thermal spectrum. In this section, we review the state of the art face detection algorithms using different methods.

3.8.1.1 Face detection based on Haar features

First robust face detection method was presented by Viola and Jones(VJ) in 2004[168].It has the ability to detect a face in real time with limited computing power. Face detector using VJ is trained using Haar features on set of face and non-face image. Afterwards, VJ detects the face in an input image through extracting Haar feature in a cascading method from multiscale for input image with applying sliding window. In each image scale and sliding windows, Haar features are extracted from the sub image and compared with Haar features of trained VJ to find the possibility of matching. Further analysis is performed by cascade when there is positive matching between extracted features and features of trained VJ. When matching is negative, sub image is rejected because it does not contain the face. VJ algorithm detects the face region in the input image when the sub image passes all the cascade steps. Face detection using VJ occurred after learning distinct Haar features, which allow to differentiate between face and non-face region of input image. This approach has the ability to detect face in video and real-time as a result of using features combination methods such as AdaBoost or GentleBoost.

3.8.1.2 Face detection based on LBP features

Cascade classifier is used with local binary patterns (LBPs) instead of Haar features[169]. LBP features require integral computations only, and LBP is more efficient than Haar features. Result reported that LBP features improve detection rate.

LBP was proposed as a features descriptor for texture in grey form. Each pixel in a grey image is compared with surrounding neighbouring pixels. Afterwards, a binary string is created after comparison made in gray image for centre pixel with neighbourhood pixels. Comparison that made binary string involve set 0 for each pixel in case this pixel has value less than centre pixel of neighbourhood pixels. Otherwise, pixel is set to 1. Centre pixel will have a value based on decimal representation of location for each value in a binary string. LBP array is created after applying this comparison for centre pixel and its surrounding pixels. Afterwards, a histogram is computed for LBP array, and normalized as pixel vectors. Pixel vectors are used as data for training and testing via the classification algorithm.

3.8.1.3 Face detection based on HOG features

Histograms of Oriented Gradients (HOG) is a features descriptor that is presented as an object detection algorithm[170]. Nowadays, it is one which is widely used in object detection including face detection. HOG features are calculated through examining gradients intensity and edge direction of an image. Gradients intensity and edge direction are represented as a local histogram. HOG features are computed by analysing image gradients and grouping them into local histograms. Afterwards, gradient orientation is converted as bins. Another grouping is conducted to make cells as blocks. Final stage is normalization blocks to as histogram block, and use set of histogram blocks as descriptor.

In order to use HOG for face detection, HOG features are calculated for training dataset, and this dataset includes images which contain face region and images that do not contain face region. Images with face region are called positive dataset, and images without face region are called negative dataset. HOG features for both positive and negative are converted as features vectors. Features vectors are used to train the classifier, which is usually support vector machine (SVM). Afterwards, trained classifier will be used to distinguish extracted HOG of future input image that contains face from one without face.

3.8.1.4 Face detection based on Deformable Parts Model

The Deformable Parts Model (DPM) is presented by Felzenszwalb in 2009[171]. This algorithm works based on using HOG and SVM in a different strategy. Felzenszwalb and his colleagues proposed that each object has a number of components such as face divided into eye, nose and mouth, using HOG features for training with multiscale on each part of the object. Training is involved on the root of the object and parts of the object. Afterwards, in detection many bounding boxes are drawn around parts and root of object. Then a non-maxima suppression technique is used to contain all bounding boxes to have one bounding box around object.

3.8.1.5 Face detection based on pixel intensity

Pixel Intensity Comparisons Organized in Decision Trees (PICO) is a new object detection approach presented by Nenad Markuˇ and his colleagues in 2013[172]. PICO is a modification of the VJ method. The concept behind this method is scanning image in different scale and positions by using cascade of binary classifiers. Instead of Haar features, PICO method uses binary pixel intensity comparisons for object detection. Each binary classifier involves a group of decision trees with pixel intensity comparisons. Decision tree is supported by GentleBoost. Every decision is made by comparison of the intensity of two pixels from the sub image. Object detection using decision tree is really fast as a result of removing feature computations.

3.8.1.6 Face detection based on thresholding

Generally, thresholding as a segmentation method is used widely in infrared thermal to extract the face region from the background. This employment is derived from the fact that the face region in the infrared thermal image is the hottest region of the image. The high temperature of face in infrared thermal is because the inner corners of the eyes are the hottest spots of the face. Based on this fundamental, many of algorithms are proposed for face detection. Paul and Blanik et al(2015) proposed a method involving face segmentation from background through applying thresholding and morphological filtering. Subsequently, centre of face that holds the high temperature is evaluated. Nose position is identified using integral projection [173, 174].

Table 3. 8: Summery of face detection methods.

Year	Methodology	Evaluation Metrics
(Fallah-Haghmohammadi and Necsulecsu 2017)	- Capturing infrared thermal - Obtain binary image using Thresholding temperature value 36.5°C - Remove noise and remain only objects that have size similar to size of face region. - Automatic template matching used to detect face region	- Not evaluated
(Reese, Zheng et al. 2012) (Kopaczka, Nestler et al. 2017)	- Foreground extraction using thresholding range. - Clustering and binarization to identify face region from background with using eyebrow as cold spot in face - Edge enhancement with difference between eye and eyebrow.	- Not evaluated
(Friedrich and Yeshurun 2002)	- Foreground extraction using thresholding. - Morphology operations full holes and remove noise - Projection profile use horizontally and vertically to detect row and column that contain face region.	- Accuracy: 83.84% - TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
(Kopaczka, Schock et al. 2018)	- HOG features and SVM for detecting face in real-time.	- Not evaluated
(Reese, Zheng, and Elmaghraby 2012) (Kopaczka, Nestler, and Merhof 2017) (Kopaczka et al. 2018) (Kopaczka, Nestler, and Merhof 2017; Basbrain, Gan, and Clark 2017)	- HOG features and SVM	**HOG** - TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
	- HOG features for multi components of same object with using multi classifiers based on SVM.	**DPM** - TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
		Haar

	- Haar features with cascade classifiers.	- TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
	- Binary intensity with cascade of binary classifiers	PICO - TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
	- Texture features with cascade classifiers.	LBP - TPR:%85 - FPR:%15 - Precision :85% - Recall:100%
(Wong, Hui et al. 2012)	- Red channel extracted from RGB thermal image and convert extracted red channel to binary. - Morphology for enhance binary foreground. - Identifying different points on head and neck. Draw curve to detect face region.	- Accuracy : 94.12%

3.9 Machine Learning Classification

Artificial Intelligence (AI) has the ability to make the computer think without human intervention. Machine learning is the subfield of an AI sector. Machine learning can be defined as the ability of computers to learn to solve problems without being explicitly programmed [175]. Many studies reported that Machine learning is an essential part for developing intelligence. In the past, Machine learning was applied widely in many prediction problems, and used in various fields such as self-driving cars, speech detection and efficient web search. Nowadays, many studies proposed a new method for disease diagnosis based on Machine learning. Using Machine learning is required for preparing a dataset with known classes and splitting a dataset into two main parts: training and testing. Machine learning can be divided into the following categories as represented by Figure 3.4[176].

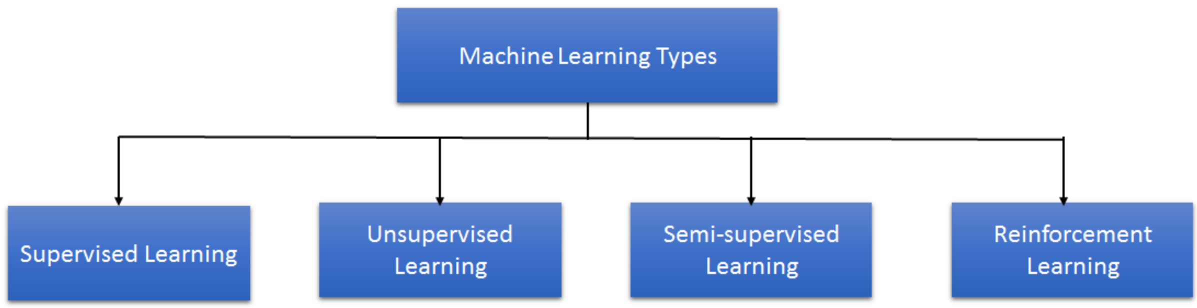


Figure 3. 4: Machine learning classification types.

3.9.1 Supervised Learning

This type of machine learning requires some customization for dataset before being applied to training. In this type, the dataset includes a number of variables, which categorize into a number of classes. This part of the dataset is called the training set. After training, trained supervised algorithm is tested on other part of the dataset for class prediction. Supervised Learning can be classified into two categories: classification and regression[177].

- The dataset as inputs are divided into different classes using classification algorithm, and the trained classification algorithm must allocate unknown inputs to these classes. This is called multi- labelling process. For example, the spam filtering is a classification process; in this process the emails are classified into "spam" and, "not spam".
- The regression is another type of supervised learning, in which the outputs are continuous instead of discrete. The predictions using regression are assessed using root mean squared error (RMSE), while predictions in classification type are evaluated by using accuracy.

3.9.2 Unsupervised Learning

This type of machine learning does not require any customization from a human for dataset, and it takes the decision without training[177]. In this type, labelling is not provided in the dataset, but predictions are achieved through extracting the hidden pattern of the given data. Clustering is a well-known method for unsupervised learning.

- The clustering is an unsupervised learning method that is used to distribute the inputs into a number of clusters. These clusters are not known earlier. It builds sets on the basis of similarity.

3.9.3 Semi-supervised Learning

This type of machine learning is considered as a class of supervised learning. The learning in this type is different, it is training on a small amount of labelled data with a huge amount of unlabelled data[176].

3.9.4 Reinforcement Learning

Reinforcement learning is different from other approaches of learning in the sense inputs and outputs are not given. It explores the surrounding environment and tests various possibilities until it finds the right answer. Feedback is shown as rewards and punishments, which it is given to program and based on its drawback, a decision is made[178].

3.9.5 Classification of supervised learning

Classification is referring to as dividing the input into a number of discrete classes. The goal of the supervised learning algorithms in solving classification problems is to learn how to obtain useful information from the labelled data in order to classify unlabelled data. Supervised learning is categorised into two types of classifiers: linear and nonlinear classifiers. Supervised machine learning algorithms that deal with classification problems involve : Linear Classifiers, Logistic Regression, Naïve Bayes Classifier, Perceptron, Support Vector Machine; Quadratic Classifiers, K-Means Clustering, Boosting, Decision Tree, Random Forest (RF); Neural networks, Bayesian Networks and so on [179]. In this research, we are focusing on linear classifiers because our dataset is going to involve two classes: stressed and healthy.

3.9.5.1 Linear classifiers

The main goal of classification in linear classifiers is to separate the group items that have similar feature values, into groups[180]. Linear classifiers use linear (hyperplane) decision boundaries to separate two classes. The linear classifier is a representation of linear function of input feature as shown in the equation below:

$$g(x) = w^{\mathrm{T}}x + b \qquad (3.9)$$

where w is weight vector, b mean bias. As example for linear classification, let us assume class (1) and class (2) are input vector feature$x$. Input feature x will be class (1) when *g(x)*>=0, and it will be assigned to class (2) if *g(x)*<=0. Based on this fundamental, many traditional classifiers were proposed such as Linear Discriminant Analysis and Logistic Regression [181].

3.9.5.2 Support Vector Machines (SVM)

Support vector machines (SVM) belongs to the supervised learning type, which has the ability to analyse datasets. It is used heavily for both regression and classification tasks. The basis of SVM is first presented in 1963 by Vapnik, Lerner, Chervonenkis. In the following years, many enhancements conducted in SVM to solve linear and nonlinear classification and regression problems. Now, it is the most well-known and used algorithm that provides a unique way for separating input features. The work mechanism behind SVM can be illustrated in Figure 3.5.

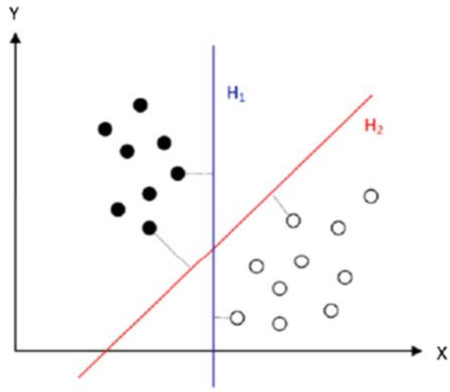


Figure 3. 5: Machine learning classification types[15].

As shown in Figure 3.5, black dots mean class (1), and white dots mean class (2). H1 and H2 are represented hyperplanes that are used to separate class (1) from class (2). In addition, there are two possibilities for fitting hyperplane to separate both classes. However, it is required to find the best hyperplane that refers to the largest distance between the two classes. SVM used margin with long distance between the hyperplane and two classes in order to separate two classes perfectly without misclassifying any input[182].

In linear classification, input features can be separated by line using equation (1) for the first group and equation (2) for the second group:

$$ax + by \geq c \tag{3.10}$$

$$ax + by \leq c \tag{3.11}$$

After fitting the optimal hyperplane, only the data points closest to the hyperplane will have a positive weight, while other data points will have zero. Data points that are closest to the decision surface are called support vectors. The location of the hyperplane is moved when the support vectors are removed. The distance between the data point (x0,y0) and the straight line $ax + by + c = 0$ can be measured using the equation below:

$$\frac{ax_0 + by_0 + c}{\sqrt{(a^2 + b^2)}} \tag{3.12}$$

In this case, the hyperplane can be computed as shown in equation (3.13):

$$x.w - b = 0 \tag{3.13}$$

while H1 and H2 can be computed as described in equation (3.14) and in equation (3.15) respectively:

$$x.w - b = 1 \tag{3.14}$$

$$x.w - b = -1 \tag{3.15}$$

where b and w mean bias and weights, x and y refer to data points, and c means support vector.

3.9.5.3 Bayesian Networks

Bayesian Network (BN) is a graphical interface for possibility relationships among of set of features. Bayesian Network is different from other algorithms through finding the relationship among features. The problem with Bayesian Network is that it is not appropriate with a dataset including many features. Thus, it is useful to conduct an exercise before starting to use it. Structure of a Bayesian network can take the following steps:

1. Identify the node that has no parents; this is called the root node.
2. Identify the node that is a leaf node, which has no children.
3. Identify the node which is a direct source or direct outcome of another node.
4. Identify the node that is not directly connected to another node.
5. Identify two independent nodes.

3.9.5.4 Decision Trees

Decision trees is a very powerful, fast and simple machine learning algorithm. It works based on a binary tree. The most important feature of Decision trees is providing a classification result in a very fast way with little training time. The working idea behind decision tree is breaking classification task down to a number of choices for each feature vector. It starts with root of tree and progresses down to the leaves until classification is made. In this algorithm, information theory is used in some form in order to obtain features that can be used to construct a series of "if/then" rules. However, the disadvantage of this algorithm is sensitivity to the missing values of input features. Another disadvantage is its inability to obtain the relationships among input features. Thus, ERID algorithm is suggested to use due to it being accurate in decreasing some missing values of dataset. Decision trees can be written as follows[182, 183]:

1. It starts with using ERID algorithm to find missing values of input features, to obtain correlations among input features, and to establish a new information system from dataset.
2. After establishing a set of features values, each input feature checks to find if it belongs to which class through using possible divisions of set features to homogeneous subsets.
3. Assess the quality of each of the homogeneous subsets according to the previously accepted condition and select the best one.
4. Divide the set of features on the basis of step 3
5. Repeat above steps for each subset.

3.9.5.5 K-Nearest Neighbour

K-Nearest Neighbour (K-NN) is the simplest classification algorithm[184]. KNN is so simple that it doesn't do any actual learning. It is a heavily used algorithm especially in developing computer vision algorithms such as breast classification[185] and dry eye disease[186]. The basic idea behind KNN is the distance between feature vectors, and is based on closest distance, class will be issue for input feature vector. Distance can be computed by using distance metric/similarity function. Assigning to class is based on the highest votes for input feature. The main issue with KNN is that it is required to determine K which means the number of nearest neighbours. KNN can be written as follows:

1. Load the training and test data.

2. Choose the value of K
3. For each point in the test data:
    - find the Euclidean distance to all training data points
    - store the Euclidean distances in a list and sort it
    - choose the first k points
4. - assign a class to the test point based on the majority of classes present in the chosen points.
5. End

3.9.5.6 Random forests

Random forest is an enhancement of Decision trees. Randomness with multiple decision trees can improve classification accuracy. This algorithm was introduced by the late Leo Brieman in 2001[187]. Random forest is different from other algorithms such as k-NN, Logistic Regression, SVMs, and decision trees. It is a type of machine learning algorithm that uses an ensemble classification method instead of a single classifier. In this case, multiple decision trees are constructed as forest and use forest to make prediction. As you can see in the Figure 3.6, random forest consists of multiple decision trees combined together. Each decision tree has voting regrading final classification. Based on voting, final classification is chosen.

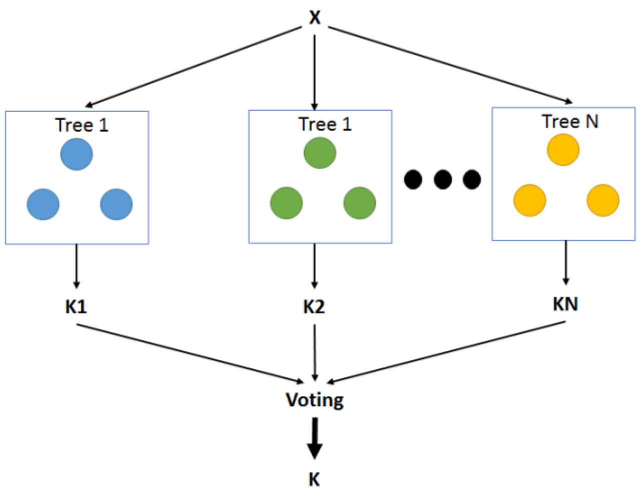


Figure 3. 6: Random forest algorithm.

3.10 Evaluation Metrics Techniques

In machine learning field, the performance evaluation metrics are significant to evaluate the performance for classifier. Many of researchers proposing the using accuracy and false positive rate for assessing the error rate classification, but other researches proposed by Davis et al [188] and Kotsiantis [189] suggested that false positive and accuracy are not enough and the results can be inaccurate. They recommended using precision, recall, accuracy, ROC and AUC as best evaluation metrics [190].

3.11 Confusion Matrix

The evaluation method is achieved using a confusion matrix (also known as a contingency table). The contingency table has four parts: True Negative (TN), True Positive (TP), False Negatives (FN) and False Positives (FP). TN and TP refer to accurate classifications of the negative inputs and the accurate classification of positive inputs respectively. Furthermore, FN means the positive input is incorrectly classified as negative type, whereas FP refers to negative input, which is incorrectly classified as positive type. Table 3.10 shows how the performance evaluation measurements computed.

Table 3. 9: Performance metric calculations

Metric	**Computation**
Sensitivity	$TP/(TP + FN)$
Specificity	$TN/(TN + FP)$
Precision	$TP/(TP + FP)$
F1 Score	$2 * (Precision * Recall)/(Precision + Recall)$
Youden's J statistic (J Score)	$Sensitivity + Specificity - 1$
Accuracy	$(TP + TN)/(TP + FN + TN + FP)$
Area Under ROC Curve (AUC)	$0 <= Area\ under\ the\ ROC\ Curve <= 1$
ROC	sensitivity vs (1 − specificity)

According to the confusion matrix, there are several measurements that can be developed to examine the performance in terms of accuracy as shown in formula (3.16) below.

$$AC=\frac{TP+TN}{(TP+FP)+(FN+TN)} \tag{3.16}$$

The main goal of using equation (3.17) is to assess the percentage of positive type.

$$TP = \frac{TP}{(TP+FN)} \tag{3.17}$$

The False Positive that was classified incorrectly can be achieved from the following equation (3.18).

$$FP = \frac{FP}{(FP+TN)} \tag{3.18}$$

Equation (3.19) was performed to measure if negative type is classified correctly.

$$TN = \frac{TN}{(TN+FP)} \tag{3.19}$$

The False Negative refers to negative inputs that are incorrectly classified as positive type. The formula (3.20) shows how FN is calculated.

$$FN = \frac{FN}{(FN+TP)} \tag{3.20}$$

3.12 Applications

In this section, we review some of the infrared thermal CAD applications that extract multiple features from face and eye regions in order to achieve their goal. These applications include detecting stress, fever and infection in human. Some of them integrated different physiological features with thermal features and use these features to develop an automated system, which is used later on in medical diagnosis.

3.12.1 Fever and infection diagnosis

Normally, humans have fever as a result of illness or particular inflammation. Conventionally used methods for measuring body temperature are applied through placing tools in the mouth and ear. These traditional methods are highly accurate, but they are time consuming, invasive and require a qualified tester[191].

Due to distinct features of IRT such as fast obtaining of temperature, non-invasive and safe, it is used extensively to detect people with fever. IRT confirmed that it is reliable in fever detection in humans. Fever detection is conducted through using IRT for measuring temperature of skin surface for forehead, face and neck[192]. Other studies confirm that the best region to measure temperature is the inner canthi region of the eye from the face region, and the best threshold temperature was 34.6 °C[191].

Figure 3. 7: Examples of fever detecion[191].

In consistency with this study, fever as a result of seasonal influenza can be detected also through placing a fixed size array on the face region around the inner corner of the eye. Subjects with temperature above 36.5°C mean they have fever[193]. Many studies confirm a correlation between human skin temperature and body core temperature[126].

Recent study [194] stated that temperature of skin surface from face region can be extracted automatically and in real time through using visual and IR camera. It started with capturing visual and IR frames for one subject in the same orientation and position. Afterwards, image alignment that involved scaling and cropping was used in order to unite dimensions of two frames. Last stage is face detection and temperature measurement. Another study investigated developing an automated system for fever detection after applying face detection and threshold temperature in the range 37.8C at morning and 38.3C at evening for detecting fever.

On the other hand, other study showed that combining visual with IR image lead to obtain heart and respiratory rate as well as body temperature[195]. As shown in Fig, capturing these physiological features is used to develop an automated CAD system for detecting infection such as Influenza. In this study, ROI was placed manually on the nasal area of the face region to capture respiratory rate through monitoring the colour changing of infrared thermal from the nasal region. Also, colour changing of visual image is used to measure heart rate. Lastly, facial temperature is captured by setting ROI on face region. Facial temperature, respiratory and heart rate are used as features to train logistic regression discriminant analysis. Trained classification model is used to distinguish between patients with infectious influenza and healthy subjects. Results were shown that facial skin temperatures of the influenza patients were 34.6 °C, and healthy subjects were 35.3 °C.

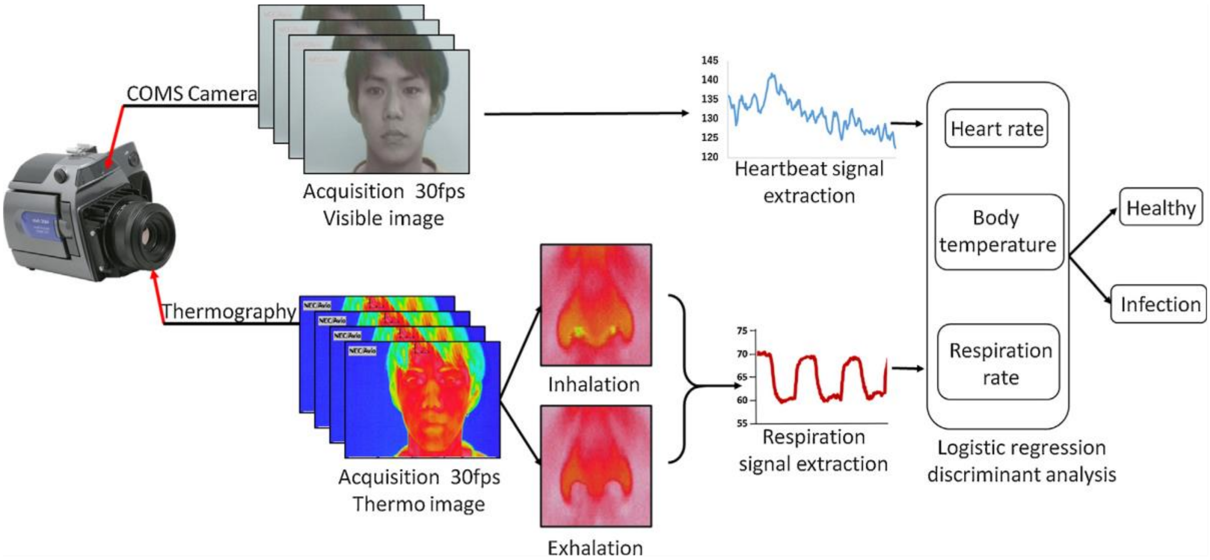


Figure 3. 8: Influenza detection CAD system using visible and thermal image processing with classifcation model [195].

Details of studies that used infrared thermography camera for developing CAD systems for fever and infection detection shown in table. After reviwing many studies, the following facts have been noticed:

1. Infrared thermography is a reliable tool in fever detection.
2. Developing automated system for fever detection is required using computer vision and image processing in order to conduct face detection and temperture extracting from face.
3. Measuring core temperture required identifying ROI , which includes forehead, ear region and inner canthus of eye. Recent study[196] confirms that the most accurate part to measure human body temperature is at the inner canthus of the eye. This spot of the eye is the warmest area on the head, and it is considered as the most stable area, when ambient temperature is changing.
4. Machine learning can be used to develop an automated system which has the ability to classify subjects to : healthy and sick.

5. Accuracy, sensitivity and specificity are used regularly to assist CAD system accuracy.

Table 3. 10: Summery of Automated system based on Infrared thermography.

Year	Methodology	Evaluation Metrics
(Selent et al. 2013)	- Manual use OptoTherm Thermoscreen, FLIR Thermo Vision 360, and Thermo focus 0800H3 with comparison with to traditional thermometry - screening face, neck and forehead - threshold value for fever detection	-sensitivity - specificity - ROC
(Ng and Acharya 2009)	- Manual ROI inner canthi region of the eye. - threshold temperature was 34.6 °C	-93% accuracy -85.4% sensitivity -95% specificity
(Ng and Acharya 2009)	- use image processing of IRT to measure respiratory and heart rates - manual ROI nasal area to obtain respiratory rate - manual ROI centre of face region to heart rates	- Not evaluated
(Yao, Sun et al. 2015)	- use image processing facial temperature, heart and respiratory rate - automatic screening face region - train six classifiers	Best classifier : SVM -9.8% Error rate -93% sensitivity -85% specificity
(Nakayama et al. 2015)	- use two type of image :visual and IR - image alignment: visual and IR image - automatic face localization - Max temperature extracted from face region	-100% sensitivity -70% specificity
(Sun, Saga et al. 2014)	- Fixed size array (48 × 47 = 2256 pixels) place on face region around the inner corner of the eye. - Threshold temperature 36.5°C	-80% sensitivity -93% specificity
(Yao et al. 2015)	- Capturing infrared thermal - Obtain binary image using Thresholding temperature value 36.5°C - Remove noise and remain only objects that have size similar to size of face region - Automatic template matching used to detect face region - Use threshold 37.8C at morning and 38.3C at evening for detecting fever	- Not evaluated
[196]	- Face detection using human shape model - Eye detection using Viola–Jones algorithm Viola–Jones algorithm - Cropped eye region - Canthus detection from eyes region - Extract temperature and use fuzzy logic to classify fever to 3 classes	-80.68% accuracy for flue case - 80.72% accuracy for health case

(Somboonkaew et al. 2017)	- Face detection using OpenCV Haar Cascades detection - Obtain temperature from centre of face region - Max and Min temperature obtain from captured IR image using Tesseract OCR - Use threshold temperature value 36.4 °C for detecting fever	- Not evaluated
[195]	- use two type of input images :visual and IR - Obtain respiration rate by manual placing ROI on nasal area, measuring temperature change around nasal area in IR image. - Obtain heart rate by monitoring colour changes in visible facial image. - Obtain facial temperature using Fixed ROI on face - Establish a classification model based on the three captured vital signs.	- Sensitivity:87.5 - Specificity: 100%

3.12.1 Stress detection

Humans under stress face different changes in nervous, cardiovascular, endocrine, and immune systems[197]. Moreover, many medical studies reported that there are realtionships between stress and disease such as cardiovascular disease, upper respiratory diseases, immunodeficiency and depression[197, 198]. In addition, the human body may face the following physiological changes, which include rising in blood pressure, perspiration and heart rate as well as vasoconstriction and paling or flushing in the face[199].

Many studies have succeeded in using an infrared thermal image for stress diagnosis through observing physiological changes of the human face via infrared thermal camera. Distinct facial thermal patterns are created as a result of different physiological activities. After observation for thermal video of subjects under stress, it is noticed that a subject who is under stress has a high-temperature value in the region around the eyes and forehead due to heat dissipation affected by increased blood flow[200, 201].

Recent research has used temperature of the eye region to develop an automated stress detection algorthim. In this study[202], physolgical signs combine with thermal features to preprare dataset for stress detection. Dataset is used to train decision tree classifer , and this dataset involves features for subjects under stress and subjects without stress, and these features involve: heart rate, respiration rate, skin conductance, and peripheral skin temperature.

Thermal features are used to detect temperture changes in eye region for subjects under stress and without stress. In order to extract thermal features, face segmentation is applied manually, and tracking algorthim is applied to track detected face region.This is followed by mutiplying orginal image with binarized image. After applying croping, RGB image is converted to HSV pixel representation. High intestity inner canthus for eye region is extracted using simple thresholding. Fig1 shows the process of locating thermal features. Average temperature includes overall minimum and overall maximum temperatures used as thermal features. Trained model showed the ability to detect stress with accuracy rate 75%.

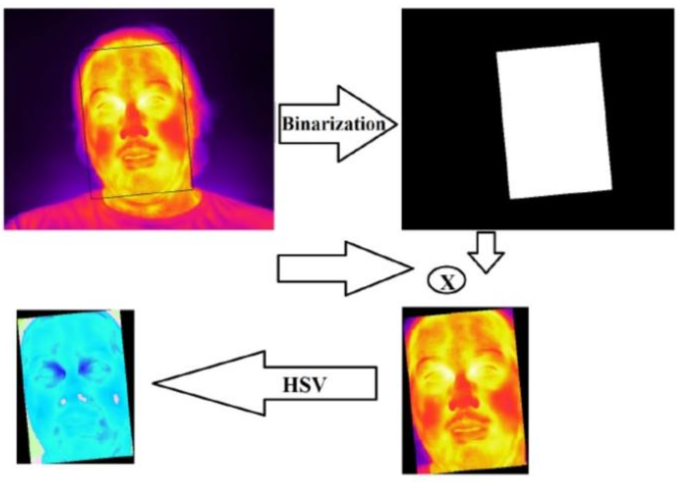


Figure 3. 9: Stress detection system using thermal image processing.

3.13 Proposed Methodology

As mention in problem statement section, stress has negative effects on meat quality, and there is no automatic system for detecting stress of an animal pre-slaughter. After reviewing many studies, the researcher proposes an automated system for stress detection by using Infrared thermography. The proposed system will have the following components as illustrated in the flow chart below.

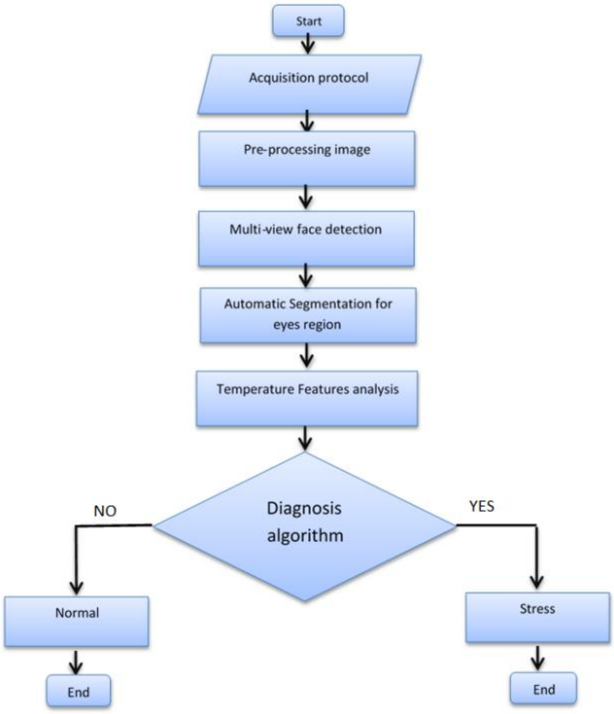


Figure 3. 10: The proposed Methodology for stress evaluation in cattle.

As shown in the flowchart above, proposed system starts by captured image from camera for target animal. Firstly, captured image converts to grey image. Afterward, captured image is enhanced by using histogram calculation. Image that is obtained will be for head region. In segmentation process, eyes will be segmented automatically by using new proposed method. Segmented region will be analysing to obtain mean, max and min of temperature, and these features will be stored in a database. Extracted thermal features will feed classifiers and use classifiers to decide whether cattle are under stress or not. In the next sections, researcher will explain in detail the components of the proposed system.

3.13.1 Acquisition protocol

Proposed system requires establishing an Infrared thermal camera in the abattoir in a position that will enable it to take a picture of cattle heads with clear vision for eyes region. Captured image will convert it to grey format due to useful for quantitative analysis [203].

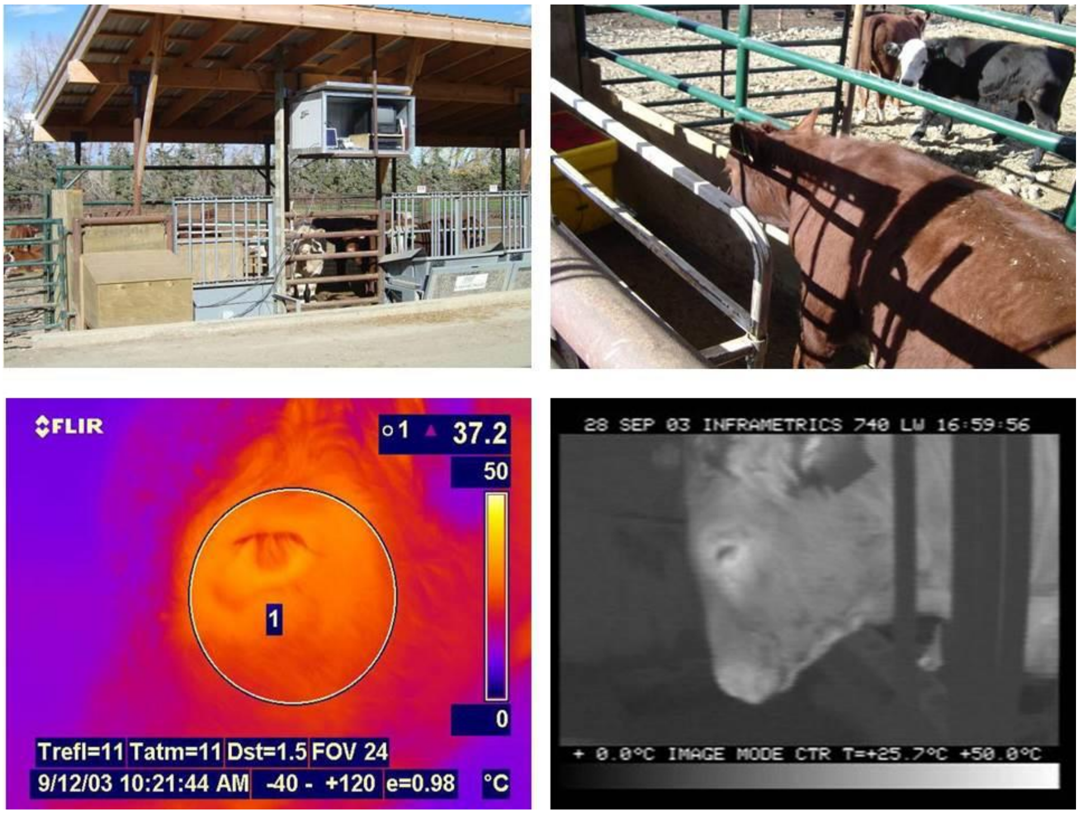


Figure 3. 11: Infrared thermal images collection[217]

The distance measured between animal and camera should be close enough so that it does not have an effect on image resolution [204]. Selected camera should be with a resolution which is more than 80x80. In some cases, changes in temperature more than 2.2C is considered the difference between healthy region and disease region. Thus, sensitivity with 0.1°C is sufficient for the camera to detect the variations. Camera should be able to include emissivity data of measured animal, distance and ambient temperature[204].

3.13.2 Pre-processing

Captured infrared image requires enhancement by reducing undesirable radiation from other sources, by using methods like Histogram equalization to remove irregular background that could lead to undesirable lighting in Infrared image [129]. This method could enhance pixel intensity values for further processing in subsequent processes. This initial task in the system is necessary for subsequent tasks of the proposed system.

3.13.3 Multi-view Face detection

Face identification is essential in order to perform eye segmentation. Face identification can be accomplished by using machine learning with features extraction technique or segmentation-based thresholding. Due to cattle being different from humans by keeping roaming, multi-classifiers are proposed to detect face of cattle to overcome changing in face position and orientation. Multi-view face detection leads to improved eye segmentation as a final result.

3.13.4 Automatic Segmentation

The most important task in our system is automatic segmentation of eyes from animal face. Our goal in this stage is segmenting the whole eye muscles from the rest of the image. For this regard, researcher expected to test well-known methods in literature for segmenting hot region such as K-mean clustering and Fuzzy K-mean clustering [132]. Researcher tested these algorithms because the eye region in cattle is the warmest region similar to the eye region in humans [155]. Researcher did not use snake algorithm with Gradient factor flow because it applied only on segmented eyes only, while our research goal is segmenting eyes from face region in cattle. However, in case test methods did not provide good results, researcher expected to develop a new method for eye segmentation.

3.13.5 Temperature Features Analysis

The next task after segmentation of eyes region is measuring temperature of eyes by using infrared thermal image. Every pixel of segmented region in grey level represents temperature value. [121] reviewed different methods for temperature measurement of eyes region in infrared image format. The most know method is mentioned by [205] and used average max and min cornea temperature in humans between ranges 32°C to 36°C with gray image in the range 0 to 255 could be computed by using the following equation (3.21):

$$T_c = T_{min} + \left(\frac{T_{gray}}{T_{High\_gray}} (T_{max} - T_{min})\right) \tag{3.21}$$

where T_c is the calculated temperature according to thermal value of the infrared thermal image. T_{min} and T_{max} refer to maximum and the minimum temperature value of the thermal camera. T_{gray}represent pixel intensity of grey image. T_{High_gray} is the high intensity of grey image which, in most cases, is 255. This equation is used to compute average temperature of the cornea. Researcher will consider 0.98 for animal emissivity and temperate to obtain accurate temperature value[206].

3.13.6 Diagnosis algorithm

The last process is diagnosis algorithm, which involves the last decision whether animal is under stress or not. The procedure of diagnosis includes dataset for IR temperature for eyes region split into two classes: stressed cattle and healthy cattle. Dataset will include a number of cattle under stress and healthy cattle. The classification algorithm will confirm that each animal is under stress or not based on infrared thermal features.

3.14 Conclusion

This chapter has elaborated on the Infrared Thermography and it is applications in disease diagnosis. Different kinds of methods with a further explanation of different techniques and are explained in this chapter. It has provided a brief introduction of Infrared Thermography and Computer-Aided Diagnosis system (CAD). Then this chapter reviewed CAD components in detail with highlighted CAD applications in stress, fever and infection diagnosis. These CAD systems work based on identifying face and eye region automatically; for this reason, many face and eye detection and segmentation methods are reviewed with a focus on methodology and results. Finally, proposed method is elaborated based on previous studies. The next chapter will discuss the first component of proposed method, face detection in detail with result and analysis.

Chapter 4 Multi View Face Detection in Cattle

4.1 Introduction

This chapter presents a novel methodology for the multi-view face detection stage of automated stress detection in cattle. The aim of this stage is to find cattle face, which is the region of interest or in other words, identify the important region of the image. Face region will be used later in the next chapter for eye localization. Overview of the proposed multi-view face detection algorithm is presented in section 4.2. Afterwards, the details of data collection and cleaning are provided in section 4.3. In section 4.4, pre-processing is explained in detail that is necessary before training and testing. Feature extraction using Histogram of Oriented gradient is presented in section 4.5. Classification that includes training and testing is presented in section 4.6. Results of face detection in term of accuracy is presented in section 4.7. Results discussion with statistical details is illustrated in section 4.8. Summary of whole chapter in the last section, 4.9.

The work presented in this chapter[207] are published as book chapter in springer database.

4.2 Background

Infrared thermography technology (IRT) is a non-invasive method that has been used to calculate and display temperature as an image. IRT can detect the variations in temperature and detect blood flow through determination the changes in body temperature [208, 209]. Several distinct features of infrared thermography make it the best choice for medical use. IRT is a fast method that visualizing temperature as an image in real-time without influencing local temperature. Also, it is non-invasive, non-contact approach and 100% side effect free. Thus, the clinical public in the US presented infrared thermography as a medical imaging tool can be used for diagnostics purpose [126, 127].

In the past decade, the enhancement in object detection and infrared thermal imaging have played a vital role in improving the medical sector. Using face detection lead to develop several automated systems for fever [194] and infection detection [196]. In addition, detecting face automatically used for obtaining body temperature, respiration rate and heart rate[195]. All of these applications of using infrared thermal imaging required to identify face region first as Area Of Interest (ROI) through applying a face detection algorithm. Many face detection algorithms developed by using machine learning algorithms, which include features extraction and automatic classification. These algorithms involve Viola and Jones (VJ), local binary patterns (LBPs), Histograms of Oriented Gradients (HOG), Deformable Parts Model (DPM), and Pixel Intensity Comparisons Organized in Decision Trees (PICO).

In the veterinary sector, Infrared thermal images used manually only for monitoring and evaluation of cattle's health for early detection of rising body temperature that is a sign of fever or local inflammation. As examples for veterinary application [2], IRT has successes in detection different disease such as mastitis in cattle, inflammation, and stress evaluation in cows, detect different diseases and infections, feed efficiency in cattle. For developing any future automated system, it required to detect face automatically in cattle.

In the current studies, two classifiers used in preparing face detection system in human: frontal face classifier or side face classifier. Frontal face detection in human required to collect images for human face in this position with a different orientation, and the same procedure applied with side face detection. Another limitation with current studies is false detection problem, which means detecting a face, but the face is not there. False detection leads to impact negatively on the accuracy of the face detector[210-212].

In animal for general and cattle in specific, it is not useful to use one or two classifiers because cattle are usually roaming in the field, and as result of this movement, animals face change in different angles and positions. For this reason, there are several variations in nose and eye shape in the frontal face position. In frontal face position, nose shape is different when cattle rise head compare to cattle when it's far from the camera. Also, it different when cattle put its head down, that hide nose with shown parts of eyes. However, the main contribution of this study is developing an algorithm for multi-view face detection in cattle with enhancement of the accuracy of the detection rate. Multi-view face detection is achieved through using three classifiers, which are established by using Histogram Oriented Gradient (HOG) as features and Support vector machine (SVM) for classification. Accuracy enhancement for face detector is conducted through using temperature thresholding, which minimizes false detection significantly. However, the main contribution of this paper is developing an algorithm for multi-view face detection in cattle with enhancement the accuracy of detection rate. Multi-view face detection achieves through using three classifiers, which are established by using Histogram Oriented Gradient (HOG) as features and Support vector machine (SVM) for classification. Accuracy enhancement for face detector conducted through using temperature thresholding, which minimizes false detection significantly.

4.3 Current Research

There is a lack of literature in developing a face detection algorithm and using it in the infrared thermal images, while a very large number of studies have proposed many face detection algorithms for the visual spectrum image. The reason for this lack is all current methods are based on machine learning, which includes features extraction and automatic classification. Face detection based on machine learning requires manual annotation for face region of the very large number of images. This number of images is not available for infrared thermal spectrum [210]. In this section, the most well-known face detection methods in thermal spectrum are selected, which are presented and discussed below.

First robust face detection method was presented by Viola and Jones(VJ) in 2004[168]. It has the ability to detect a face in real time with limited computing power. Face detector uses VJ trained using Haar features on set of face and non-face images. Afterwards, VJ detects the face in the input image through extracting Haar feature in cascading method from multiscale for input image with applying sliding window. In each image scale and sliding window, Haar features are extracted from the sub- image and compared with Haar features of trained VJ to find the possibility of matching. Further analysis is performed by cascade when there is positive matching between extracted features and features of trained VJ. When matching is negative, sub- image is rejected because it is not containing face. VJ algorithm detects the face region in the input image when the sub- image passes all cascade steps.

Cascade classifier is used with local binary patterns (LBPs) instead of Haar features [213]. LBP features require integral computations only, and LBP is more efficient than Haar features. Result reported that LBP features improve detection rate. LBP was proposed as features descriptor for texture in grey form. Each pixel in grey image are compared with surrounding neighbouring pixels. Afterwards, binary string is created after comparison made in gray image for centre pixel with neighbourhood pixels. Comparison that made binary string involves set 0 for each pixel in the case that this pixel has value less than centre pixel of neighbourhood pixels. Otherwise, pixel is set to 1. Centre pixel will have a value based on decimal representation of location for each value in the binary string. LBP array is created after applying this comparison for centre pixel and its surrounding pixels. Afterwards, histogram is computed for LBP array, and normalized as pixel vectors. Pixels vectors are used as data for training and testing via classification algorithm.

Histograms of Oriented Gradients (HOG) is features descriptor that is presented as an object detection algorithm[170]. Nowadays, it is one most widely used in object detection including face detection. HOG features are calculated through examining gradients intensity and edge direction of image. Gradients intensity and edge direction are represented as local histograms. HOG features are computed by analysing image gradients and grouping them into local histograms. Afterwards, gradient orientation is converted as bins. Another grouping is conducted to make cells as blocks. Final stage is normalization blocks to as histogram block, and use set of histogram blocks as descriptor. In order to use HOG for face detection, HOG features are calculated for training dataset, and this dataset includes images which contain the face region and images which do not contain the face region. Images with face region are called positive dataset, and images without face region are called negative dataset. HOG features for both positive and negative datasets are converted as features vectors. Features vectors are used to train classifier, which is usually support vector machine (SVM). Afterwards, trained classifier will be used to distinguish extracted HOG of future input image that contains face from one without face.

The Deformable Parts Model (DPM) is presented by Felzenszwalb in 2009[171]. This algorithm work is based on using HOG and SVM in a different strategy. Felzenszwalb and his colleagues proposed that each object has a number of components such as face divided into eye, nose and mouth. Using HOG features for training with multiscale on each part of object, training is involved on root of object and parts of object. Afterwards, in detection many bounding box is drawn around parts and root of object. A non-maxima suppression technique is used to contain all bounding boxes to have one bounding box around object.

Pixel Intensity Comparisons Organized in Decision Trees (PICO) is a new object detection approach presented by Nenad Marku ̌ and his colleagues in 2013[172]. PICO is a modification of the VJ method. The concept behind this method is scanning image in different scale and positions by using cascade of binary classifiers. Instead of Haar features, PICO method uses binary pixel intensity comparisons for object detection. Each binary classifier involves a group of decision trees with pixel intensity comparisons. Decision tree is supported by Gentle Boost. Every decision is made by comparison of the intensity of two pixels from the sub- image. Object detection using decision tree is fast as a result of removing features computation.

The recent study used VJ, LBPs and HOG for face detection in humans in the frontal position without eyeglasses and the results have shown VJ is accurate with average 95% compare to LBPs, and HOG. In this study, a dataset of 10,021 thermal infrared frontal face images was adopted from two common databases: NIVE and I.Vi.T.E. For performance evaluation, True, False Positive Rate and ROC curve were used to measure the performance of face detector[210]. In another recent study, comparison is made among VJ, LBP, HOG and DMP. The results have shown that VJ VJ, LBP, HOG and DMP are convergent in average of Precision, Recall, True Positive, False Positive. Database that was used in that study included 2935 images[211].

According to our investigations in the previous work, most of the current face detection methods in humans are developed for the frontal position, and little research has been done for multi-view face detection. In addition, there is no research done for face detection in cattle using infrared thermal spectrum. Therefore, multi-view face detection in cattle is crucial for any intelligent system, in which infrared thermal has ability to extract temperature remotely. In this study, HOG feature with SVM is used due to HOG-SVM having the ability to work with a small database[214]. Also, Precision, Recall, F-measure, True and False positive are used for performance evaluation.

4.4 Data Collection

The Infrared Thermography database was created by converting video with seq format to a sequence of grey images. The infrared thermal database includes 702 thermograms images which show animal face in different positions and orientations. Recording of IRT video imagery was done in a commercial abattoir in Arthursleigh farm after obtaining ethical approval. Arthursleigh farm is in Marulan town in the Southern Tablelands of New South Wales, Australia. The camera was setup at approximately 2 metres from the target cattle as they moved through the race towards the knocking box. All cattle were in the shade under the roof during the recordings, and the camera was setup at approximately 45 degrees angle from the head of the animal.

Duration of the video is two hours involving 300 cattle in different positions and orientations. There is not any kind of manipulation in the background. The images were acquired by using AGEMA 590 PAL, Therma Cam S65, A310, T335 with 320 × 240-pixel optical resolution of detectors. Preparing dataset started by extracting frames from the Infrared Thermal video. After extracting 702 images from the video, extracted images were divided into three groups; each group will be used to train the single classifier. In each group of images, software is used manually for annotation of the face region.

4.5 The Proposed Methodology

The proposed method for face detection has the following components as illustrated in Figure 4.1: pre-processing, image scanning, feature extraction, post-processing and end with placing a bounding box around the face. The outputs of each stage serve as inputs to the following stages. The proposed method for face detection starts by loading an infrared image in a grey format.

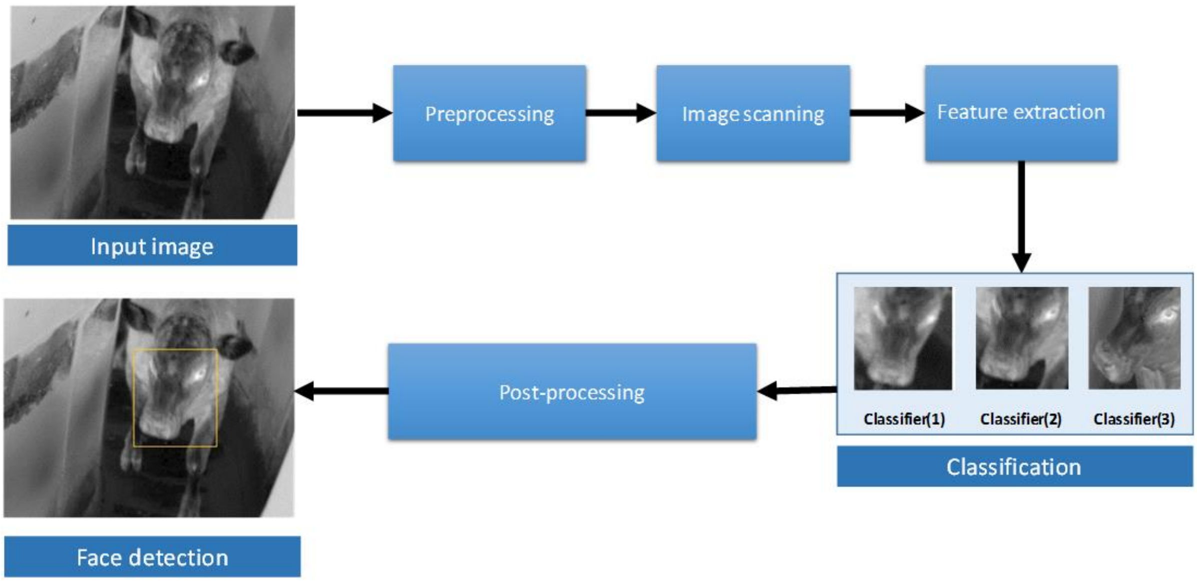


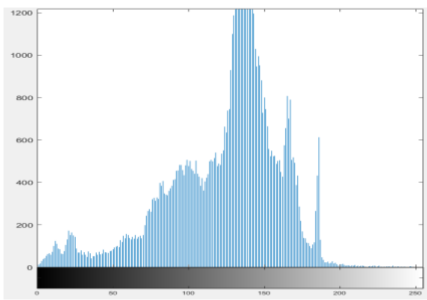
Figure 4. 1: The Proposed Face detection method includes pre-processing, image scanning, feature extraction, classification and post-processing.

Loaded infrared thermal image is enhanced in two aspects: brightness and normalization. Pre-processed image is used as input for image scanning stage. In this stage, the image is scanned entirely by using windows in different scale and size. This stage is necessary to extract features from the region of image until we find the face as the last outcome. In the feature extraction stage, Histograms of Oriented Gradients (HOG) are used as features to distinguish a face from the background region. HOG worked based on the computational calculation of intensity gradient of an image presented by Dalal and Triggs [170]. Currently, it is one of the most widely used methods for object detection. HOG is computed and converted as a feature vector and used as a feature vector for creating three face classifiers and these classifiers are used in the classification stage. Three classifiers are used to detect the face in a different orientation. Each classifier was created after training on the cattle face in a particular position. As shown in Figure 1, the first classifier is trained when cattle face is in the frontal orientation and shows a clear vision for eyes and nose. Second classifier is trained when cattle face in frontal orientation but head down, which shows part of the nose with showing eyes. Last classifier is when cattle show one eye and side of the nose.

All classifiers used Support vector machine (SVM) for training and testing. SVM is a well-known classification algorithm that is used widely in literature for classification purposes. After classification, post-processing is applied to eliminate the undesired region and leaving the face region only. The last stage is necessary to reduce false detection, which improves face detection significantly.

4.6 Pre-processing

In this stage, all input image converted to grey format and apply normalization of pixels intensity by using histogram equalization. The aim of the histogram equalization step is to normalize image brightness and contrast by modifying pixels intensity by using histogram distribution. The concept behind histogram equalization is scaling the most frequent pixel intensity value compare to other pixels values. Figure 2 presents examples of the image before and after apply histogram equalization. As seen in Figure 2, the eyes and nose of cattle face become brighter with pixel intensity reach 255. In contrast, the dark region becomes darker with pixels intensity close from 0.



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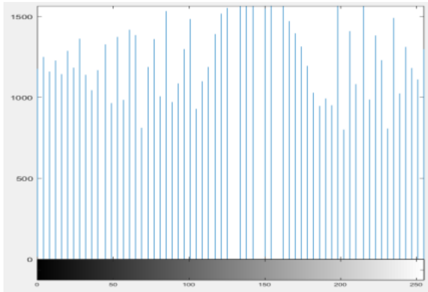

c d

Figure 4. 2: Pre-processing stage using Histogram equalization: (a) Input image with grayscale, (b) Histogram for input image, (c) image after apply Histogram equalization,(d) Histogram for processed image.

4.7 Image scanning

The aim of this stage is scanning each image at various locations and scales. The goal of the scanning is to simplify a method to localize the face in an image, regardless of where in the image the face appears and how large/small it is. There are two sub-stages in image scanning: Image pyramids and Sliding windows.

4.7.1 Image pyramids

Image pyramids are image representations on a different scale. Using an image pyramid enables us to find faces in images at different scales of an image. It starts from the original image in the bottom with original size (in terms of width and height). In each subsequent layer, the image is resized and optionally applied Gaussian blurring filter in each layer. The image is progressively resized until some stopping criterion is met, which normally is a minimum size being reached. In each resized image, a sliding window is applied searching about-face region.

4.7.2 Sliding Windows

Sliding windows are combined with the Image pyramids, and this combination leads to finding a face in images at various locations. A sliding window is a rectangular region with a fixed width and height that slides from left to right and top to bottom of each scale in the image pyramid. For each of these windows, we can take the window region, extract features from it, and apply an image classifier to determine if the window contains an object that interests us, in this case, a face. Image pyramids and sliding windows, while simple, play a critical role in object detection and image classification.

Figure 4. 3: Image sliding windows with size 64x64 across image in different scale and position till find face region.

As shown in Figure 4.3, green rectangle represents the sliding window with size 64x64 pixel. It slides in each image scale green rectangular slid from top to bottom with moving start from left to right side. In this case, if we had an image trained classifier, we could take each of these windows and classify the contents of the window until we find the face region.

4.8 Feature extraction

This step is necessary for face detection by preparing features for classification stage. Histogram oriented gradient (HOG) is used as feature for face detection. Linear Support Vector Machines is used for classification.

Histogram Oriented Gradient (HOG) is constructed with the following parameters: pixels per cell =4, cells per block=2 and orientations=9. In addition, Square root normalization is applied. These parameters work well during the establishing of classifiers. Figure 4.4 illustrates the HOG feature for cattle face.

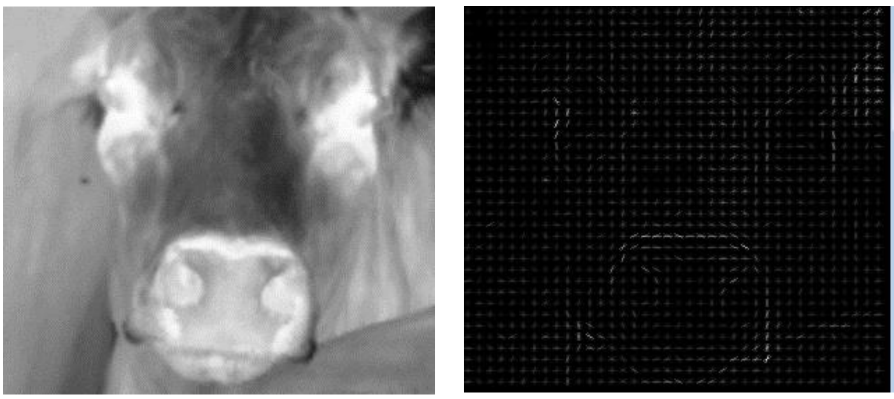

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Figure 4. 4: HOG features for cattle face: (a) Input image with grayscale, (b) HOG for input image.

4.9 Classification

In the classification stage, SVM is used for classification of the HOG features. After HOG is computed, HOG features are converted to vectors and these vectors are used in training and testing. Feature vector classifies to two classes. As these classes can be separated linearly, linear SVM is used for classification. In this study, we are using three classifiers as a result of cattle face taking various orientations and positions as explained in the next section.

4.9.1 Training and Testing

Training involve separated dataset into three groups of infrared thermal images. Data set include manual annotation for face region of image. Each group of infrared thermal images divided into training and testing. The training set includes 80% of dataset and 20% for testing, and this means for overall dataset 560 images used in training and 140 images for testing. This dataset that includes face region classified to positive. Negative region refers to image without showing face. As can be seen in Figure 5(A), training starts with using the annotated image. In this stage, we use image labeller app from Matlab for face region labelling. Afterwards, skimage library with python used for HOG extraction from face region (positive) and non-face region (negative). HOG features for both positive and negative image to convert to the list of vectors. List of vectors labelled to -1and 1, where -1 means that the feature vector is not representative face region, and a value of 1 indicates the feature vector is representative face region. After that, vectors of HOG features saved as a separated file using h5py library. SVM using this file for training as shown in Figure 5(A). This scenario applied in each group of images until creating three trained classifiers and all these classifiers saved as three separated files.

In testing, the scenario is different as shown in Figure 5 (B). It starts by image scanning by using image pyramids associated with sliding windows. HOG features extracted from each window and converted to the list of the feature vector. Feature vector tested by three classifiers to find out this vector belongs to which class. The bounding box is drawn around the face region after applying the post-processing stage as explained in the next section.

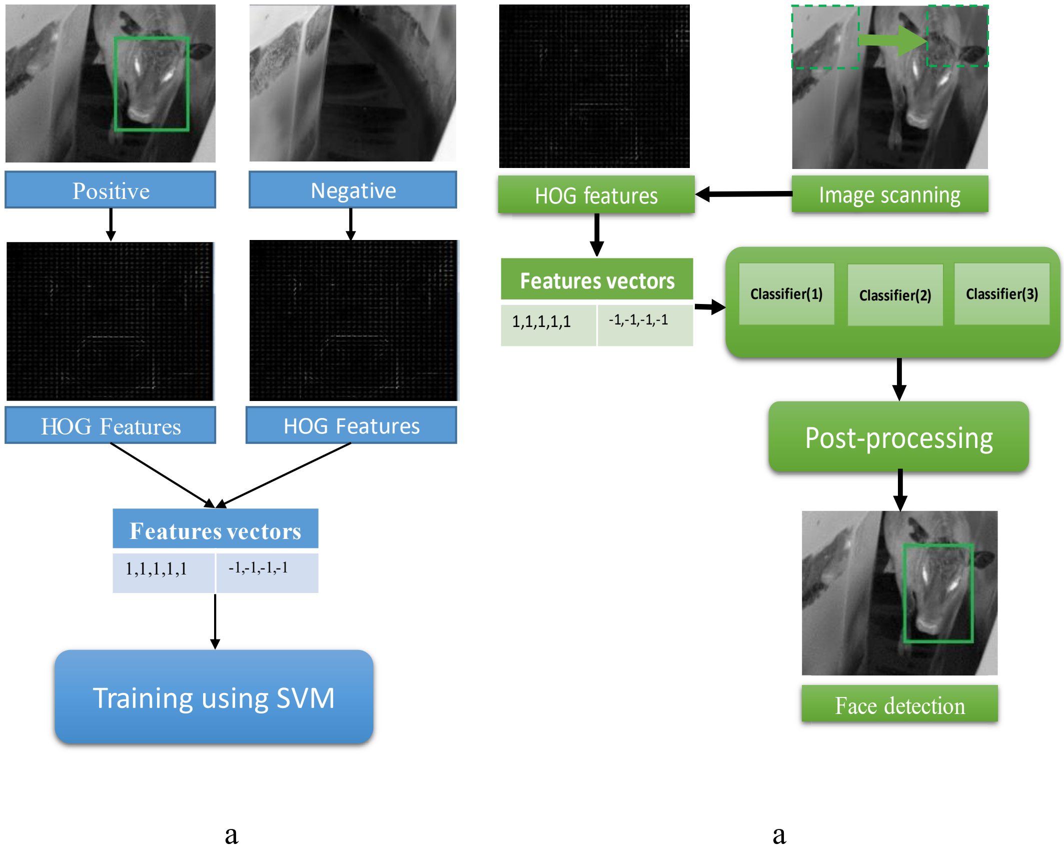
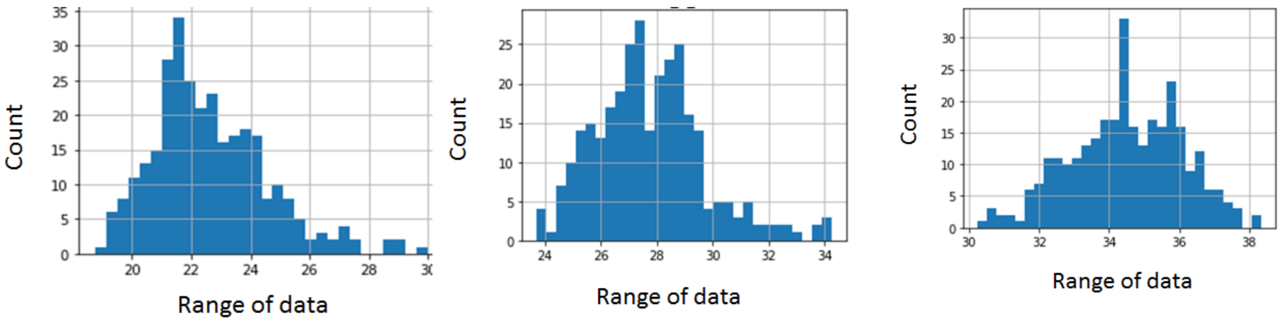


Figure 4. 5: Classification procedure: (a) Training procedure, (b) Testing procedure.

4.10 Post-processing

The last stage in face detection method is post-processing. This stage applied before drawing the bounding box around the face region. This stage is necessary for minimizing false detection and detect face region only. Normally, the eye region in the face has a temperature range of 30 to 38 Celsius. This temperature range is obtained after checking the temperature value of the eye region for 300 subjects. As can be seen in Figure 6, max temperature between 30 and 38, the mean temperature in range 24 to 34 and min temperature in range 20 to 30. In this stage, masking applied between candidature face region from the infrared thermal image and infrared thermal matrix in order to test temperature range. If the temperature range between 30 to 38 this mean candidate region could be facing. Otherwise, another region is scanned. This stage is necessary for minimizing false detection as illustrated in the result section.



a b c

Figure 4. 6: Histogram distribution of temperature values for eye region in cattle: (A) Histogram distribution for mean of minimum temperature, (B) Histogram distribution for mean temperature, (C) Histogram distribution for maximum temperature.

4.11 Results and Analysis

Proposed face detection is evaluated through applying three classifiers with post-processing stage on 143 of testing infrared thermal images. Figure 4.8 shows a sample of the testing dataset. In contrast, normally two classifiers are applied to the same testing image. These two classifiers for face detection are used in this study as shown in the literature [210, 211]. In evaluation terms for two face detection methods, Precision, Recall, F-score, True positive and False positive rate are used [215]. Precision is the measured accuracy in the case that the true negatives were also predicted as negative. Sensitivity, that is also called recall, is measured accuracy in the case that true positives were also classified as positives. F-score calculates the percentage of Specificity and Recall. These evaluation metrics are used widely to test the accuracy of classifiers. Also, the detection rate is used to measure how the proposed method detects the face region correctly. Lastly, the false detection rate is used to measure if the proposed method detects a region, which does not belong to the face region.

Precision can be calculated by using equation (4.1).

$$P = \frac{T_P}{T_P + F_P} \tag{4.1}$$

where $\boldsymbol{T_p}$ refers to true positive and $\boldsymbol{F_P}$ refers to false positive. Recall can be computed by using equation (4.2).

$$P = \frac{T_P}{T_P + F_N} \tag{4.2}$$

where$\boldsymbol{T_p}$ refers to true positive and $\boldsymbol{F_N}$ refers to false positive. F-score measures Precision and Recall by calculating the percentage between Recall and precision. A higher value of F-score refers to a better result in terms of accuracy. It can be computed with the mathematical equation (4.3).

$$F = 2 \times \frac{P \times R}{P + R} \tag{4.3}$$

Lastly, the detection rate D_R of proposed face detection method is obtained by dividing the number of images F_D where face is detected correctly by the total number of test images T_A as shown in equation(4.4).

$$D_R = \frac{F_D}{T_A} * 100\% \tag{4.4}$$

Table 4. 1: Face Detection Result.

Evaluation	**Current Method using Two classifiers**	**Proposed Method using Three classifiers**
Precision	0.98260	0.99502
Sensitivity	0.79021	0.91006
F-score	0.87596	0.95064
True Positive Rate	0.78	0.90
False Positive Rate	0.2	0.0

As shown in Table 4.1, the proposed method performs well compared to the used method in the literature. In precision and sensitivity, the proposed method has a percentage of 0.99 and 0.91 respectively compared to the currently used method. Also, the proposed method can detect face region correctly with the percentage of 0.90 compared to the current method with the percentage of 0.78. However, the current method has false detection compare to the proposed method as shown in Figure 4.7. As seen in Figure 7, the current method can detect face correctly in 114 from 143 testing images, while the proposed method can detect face correctly in 128 from 143. Besides, the current method has false detection with number 3 means it is wrong to classify the region as a face while it belongs to the background or other parts of the animal body. In the proposed method, there is no face detection, which is performing well.

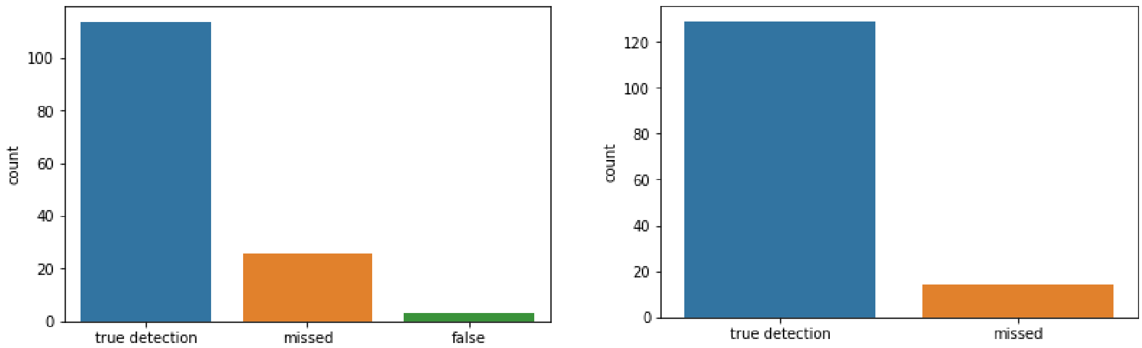


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Figure 4. 7: Face detection rate: (A) current method using two classifiers, (B) Proposed method using three classifiers.

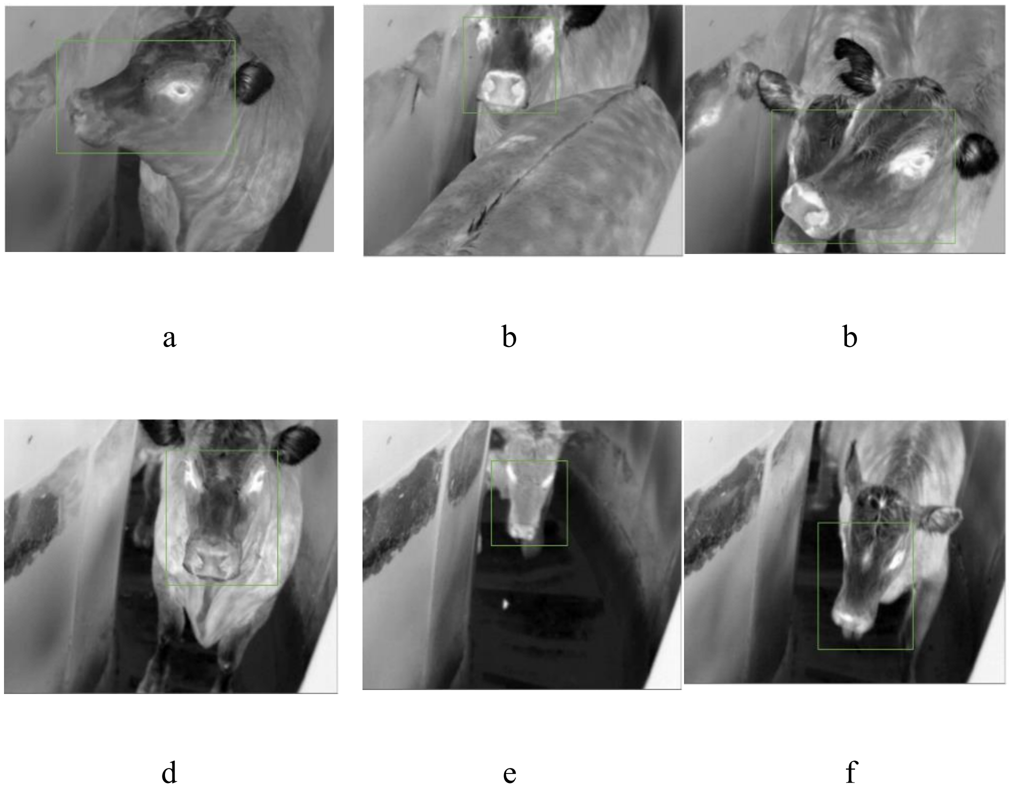


Figure 4. 8: Face detection with different posit ions: (A) Face region with side direction, (B) Frontal face with up nose, (C) Frontal face with aside nose, (D) Frontal face with clear nose and eyes , (E)Far frontal face with hidden nose, (F)Frontal face with down nose.

4.12 Discussion

According to the results, we can reach the following findings. As shown in Table 4.1, it is clearly shown that the proposed method better than the current method in term of Precision 0.99, Recall 0.91, F-score 0.95 with high True positive rate 0.90 and zero False-positive rate. Using three classifiers increase the performance of face detection as a result of the improve SVM generalization. SVM generalization enhanced because of splitting dataset as a group of sub dataset and each sub dataset used to train one classifier. In this study, author re-organize dataset in a way make similarity high with less difference, and this strategy makes the proposed method perform well compared to the currently used method in the literature. In addition, each single infrared thermal image tested with three classifiers. Post-processing stage used to reduce false detection, which improves accuracy significantly as seen in Table 4.1. In the proposed method, false detection is zero compare to 3 false detection from the current used method.

In this study, the author applied the proposed method on his own dataset as a result of there is no infrared thermal dataset for cattle to provide it in public for researchers. In addition, this is the first study proposed method for multi-view face detection in cattle using infrared thermal images with improving accuracy, and a comparison made with the currently used method.

Lastly, deep learning is not used in this study due to it requires massive dataset, and this dataset needs to involve manual annotation for face region. For example, using deep learning for pedestrian's detection in railway using infrared thermal required manual annotation for a total of 30.129 [216]. Therefore, it is recommended to prepare enough dataset in order to obtain robust face detection.

4.13 Conclusion

This chapter presents the details of the multi-view face detection in cattle. The main contribution of the proposed face detection in this study that differs from previous studies that it is the first study conducted for multi-view face detection in the indoor environment using infrared thermal images. In addition, this is the first face detection study using three classifiers, which are more powerful compared to the currently used method in the literature. Using eye region temperature to reduce false detection also improves the accuracy of face detection significantly as explained in section 4.7. According to the results of this study, the proposed method is effective with the following average 0.95064 and 0.90 for F-score and detection rate. This means that the proposed method is accurate with less error compared to the currently used methods as explained in Table.1. Constructing face detection is useful for developing an intelligent system for extracting temperature from the eyes or mouth region. Eyes and mouth region are used widely for identifying infection and disease in cattle [8]. In future work, it is intended to increase the number of images in order to use deep learning that could increase performance significantly.

Chapter 5 Automatic Eye Segmentation in Cattle

5.1 Introduction

This chapter present a novel methodology for automatic eyes segmentation in cattle. The aim of this stage is to segment eyes region from cattle face. Segmented eyes will be used later for extracting temperature, which will be used for stress evaluation as explained in chapter six. Overview of the proposed methodology for eyes segmentation is presented in section 5.3. Afterwards, the details of the first stage of proposed method which is about foreground localization are provided in the section 5.4. In section 5.5, multi view face detection is explained briefly; it is necessary for identifying Area OF Interest. The last stage is eyes segmentation which involves a number of stages and is explained in section 5.6. After eye segmentation, eye localization is presented in section 5.7, which includes drawing bounding box around eyes with temperature extraction. Results discussion with statistical details is illustrated in section 5.8. Conclusion of whole chapter is in the last section, 5.9.

Parts of work presented in this chapter are published in two conference papers [217, 218], and another part submitted to journal with high impact factor.

5.2 Background

Several studies have used a variety of measures to test the health status of animals. These tests include blood tests, rectal temperature, respiratory rate and heart rate [1]. These measurement methods are not useful for massive herds of cattle. Infrared thermography technology (IRT) is a better choice as it does not require a human being to be physically close to the animals, therefore saving time and effort. Infrared thermography technology (IRT) is a non-invasive method that has been used widely to calculate and display temperature as an image. IRT can detect the variations in temperature and detect blood flow by determining changes in body temperature[208, 219]. IRT measures the heat radiation emitted from the surface of objects[5].

IRT is often applied to monitor and evaluate animal health for early detection through rising body temperature , which is a sign of fever or local inflammation [2]. As examples of veterinary application, IRT has succeeded in the detection of different diseases such as mastitis in cattle [99], inflammation detection in animals[15], stress evaluation in cattle[220], and feed efficiency in cattle

[106]. Various studies have pointed out that the eye is the best region for measuring body temperature [8]. Temperature measurement using IRT in the eye area is well-known as a good indicator of the health status of cattle [1, 8, 19] . The eye region is used to evaluate stress and fear in dairy cows [220], horses [20], sheep [88], and elks [86]. In these studies, capturing images using the Infrared thermal camera and localizing eyes had to be done manually. Currently, up to the authors' best knowledge, there is no automated approach for eye localization in cattle, which is crucial to future automated systems in the veterinary sector. Automatic eye localization in humans is commonly implemented in several technical situations such as the biometric system [221], human interaction with a computer [222], and safety enhancement[223]. Most of the human automatic eye localization applications are based on machine learning. [20]. In machine learning, particular features are used to train classifier and trained classifier scans input image by sliding a bounding box in different sizes in order to find features that belong to a target object. Based on machine learning technology, most automatic eye localization uses image features such as Haar[224], Histogram of Oriented Gradient (HOG) [225] and Linear Binary Pattern (LBP) [226]. The main part of the image processing research path for eye localization is the segmentation.

Segmentation for the eye region is essential for effective eye localization. In this chapter, proposing an automatic eye localization is based on segmentation as it is crucial in using infrared thermography images and results in a clear image of the target object compared to conventional image processing. In addition, the proposed method is beneficial for eye detection in real time through decreased processing time. Many studies have used segmentation as the task before employing localization of the eyes for the face or other target regions. In humans, Cruz-Albarran.et.al used the constant threshold value to extract the face from the background prior to the main task of human emotion detection [227]. Another segmentation method for extracting an important region was performed based on static threshold in order to process the region that contained the face and eyes [149, 228]. Establishing temperature range manually has been used as a pre-processed segmentation method to identify the human body before performing face and eye localization [150]. Bi-modal thresholding has been used to determine the centroid of the face, which has been used for face localization in infrared thermal images with homogeneous background [229]. Otsu thresholding, and horizontal and vertical projection curves of the binary image have been implemented to determine the face region [230]. Another segmentation method is Otsu thresholding with snake algorithm to identify the face [149].

Few researchers have studied eye segmentation in animals generally or cattle in particular using infrared thermal images. Unlike human subjects, cattle are usually roaming in the field and, as a result of this movement, their faces change in angle and position. The main contribution of this work is a novel segmentation approach to automatically identify the eyes of cattle regardless of the position of the animal in relation to the camera. This proposed novel method includes foreground identification using edge difference. A new method for thresholding based on histogram processing is also proposed. After eye segmentation, eye localization and temperature measurement will be the last stage of the proposed method.

5.3 Proposed Segmentation Methodology

This section demonstrates the main process of the proposed eye segmentation, which consists of the following processes: foreground localization, noise elimination, automatic thresholding, eye segmentation, and eyes localization. The framework of proposed method is illustrated in Figure 5.1.

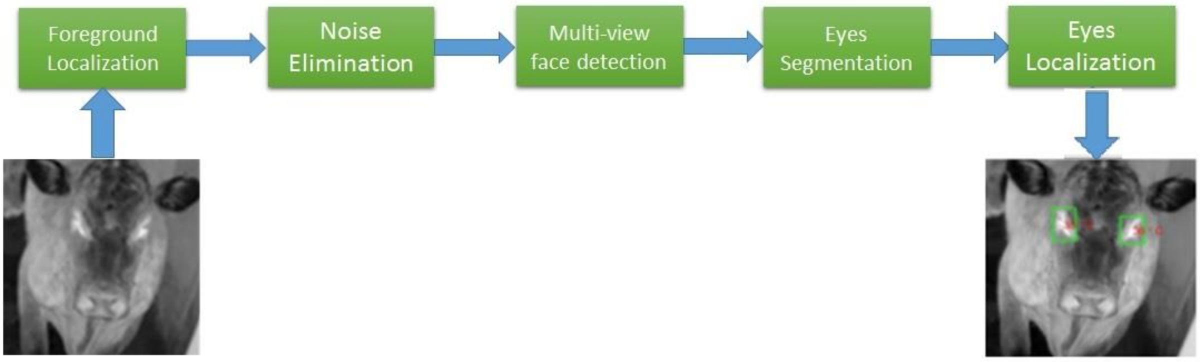


Figure 5. 1: The Structure of the proposed method

Many studies indicate that eyes are the warmest region of the human and animal face [8, 150, 217]. The concept behind the proposed method is extracting this hot spot from the animal's face. As shown in Figure 5.1, proposed method starts by converting matrix temperature to gray form. The next stage is identifying the foreground region which is represented by the animal's head and other regions of the animal's body. The foreground region includes several parts, and each part is processed individually by masking and thresholding it until all undesirable regions are removed. This procedure represents the noise elimination step. Automatic thresholding, hot spot detection and blob refinement are applied in the segmentation stage, and eye localization is conducted in the last stage. This chapter contribution is represented by the development of a new segmentation method which performs well compared to the well-known segmentation approaches of Otus, FCM and Max entropy. The proposed method is used for eye segmentation which applies a new form of global thresholding. Well-known methods, used widely in the literature, have failed to extract the eye region properly. In contrast, the proposed method works well as explained in the following sections.

5.3.1 Foreground localization and Noise Elimination

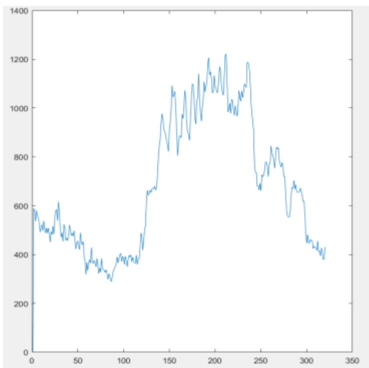
Foreground Localization is necessary for reducing the search area of the eyes. Most methods used for eye and face localization in infrared thermal employ projection curves and the Otsu threshold for foreground localization [230]. The Otsu threshold is implemented to convert infrared thermal images to binary, and projection curves are computed to identify the target region for further processing. These methods are normally used for foreground localization with homogenious background. Projection curves with Otus, fuzzy c-mean clustering or Maximum entropy failed in foreground localization as a result of heterogeneous backgrounds. In this study, a combination of the vertical projection curve, edge processing, thresholding and blob processing is used for foreground localization. Let is $f(i,j)$ is represented image in grayscale, which has the formation as defined in equation (5.1).

$$f(i,j) = x(i,j) + y(i,j) \tag{5.1}$$

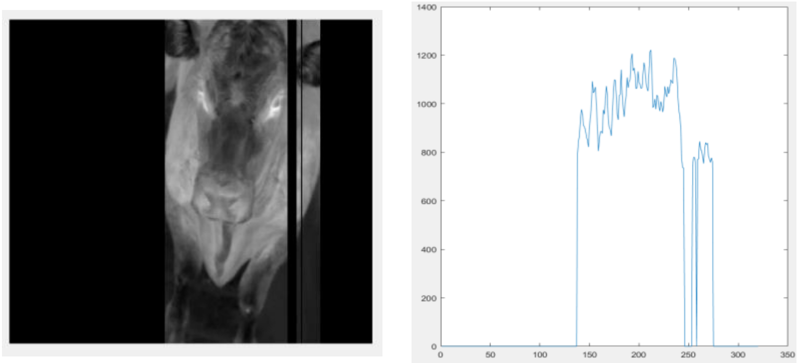
where $x(i,j)$denotes the foreground information that refers to foreground, which means animal, and $y(i,j)$represents background information. Foreground localization is a result of edge processing, which is the summation of difference between pair pixels in each column in image as shown in equation (5.2).

$$f(i,j) = \sum_{j=1}^{column} f(i,j)_{column-1} - f(i,j)_{column} \tag{5.2}$$

Due to mean operation leading to undesirable results, median operation is applied on the summation of edge processing which leads to generate foreground localization with many regions as shown in Figure 5.2. These regions include foreground region with much noise, which is eliminated using thresholding and morphology operations as explained in the next section.



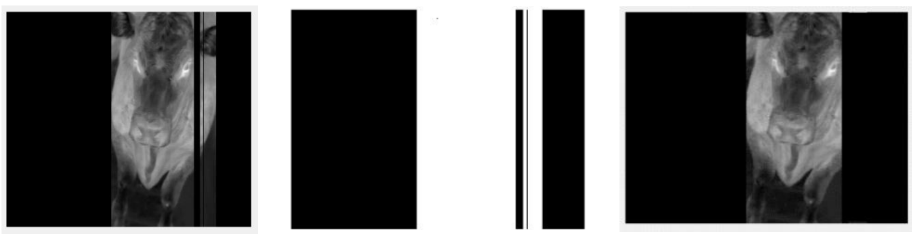
(a) (b)



(c) (d)

Figure 5. 2: Results of foreground localization :(a) original image,(b) intensity distribution in vertical direction, (c) background elimination, (d) results of median process.

As shown in Figure 5.2, after the foreground localization, all regions that are not zero are converted to binary form and each blob processed individually using Morphology and mask operation. Firstly, the number of blobs as shown in Figure 5.3 (b) are generated as a result of converting each gray region that is not zero to a region with 1 value. Morphology operation applied on each blob to give blobs with different values. Every region represent as part of gray image will be result of masking the binary region with input image in gray region. Afterwards, each gray region is processed separately with histogram equalization. Histogram equalization is used in this stage to adjust the intensities in each region. All spot with high intensity in each region will have value of 255. This value is used as the threshold, and regions that don't have a blob will be considered to be noise and be eliminated Figure 5.3(c). Only regions that have high intensity will remain as input for next stage.



(a) (b) (c)

Figure 5. 3: Noise elimination: image with foreground(a), binary image(b), final image with noise elimination(c).

The method for the noise elimination is defined as in algorithm 5.1:

Algorithm 5.1 Noise elimination procedure

1: Read infrared image with identified foreground region

2: Convert identified foreground region to binary

3: Convert gray image to number of blobs

4: For each individual blob

5: Masking blob with original gray image

6: Histogram equalization

7: global threshold

7: If count number of blob inside region = 0

8: Convert current entire region to zero

9: else

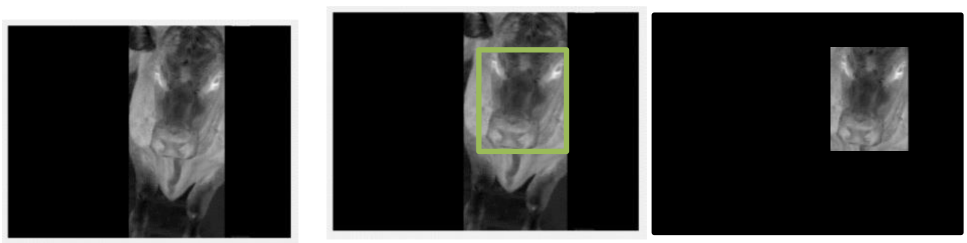
10: check another blob

11 End If

11: end for

5.3.2 Multi-view Face Detection

After the noise elimination, the proposed method for multi-view face detection is applied.



(a) (b) (c)

Figure 5. 4: Multi-view face detection: (a) image with foreground, (b) image with detecting face, (c) cropping face region.

As shown in figure 5.4, face detection applied in order to identify face region. Proposed method for face detection explained in detail in previous chapter. After applying face detection, cropping for face region is applied in order to prepare image as input for next stage eye segmentation.

5.3.3 Eye Segmentation

After the face detection, the proposed method for eye segmentation is applied. The proposed method involves several tasks as explained in Figure 4.1. Infrared image in gray form without noise using as input (as in Figure 5.3(c)) for the proposed method. It starts with global threshold. Global threshold is the process for converting the grayscale image to a binary image. A threshold was applied for dividing the image into '1' pixel (white region) and '0' pixel (black region). This process can be performed by identifying the numerical value for converting from grayscale form to binary form. Based on this concept, many methods have been suggested for determining the threshold value in infrared thermal images. An example is selecting a constant numerical value or range of temperatures based on trial and error [150]. This method is not useful as a result of changing in temperature values. An automatic threshold based on Histogram of image is used widely in many studies. The most popular methods are Otsu [231] , fuzzy c-mean method [232] and Maximum entropy [233]. After applying these methods to our infrared thermal image database, these methods generated a lot of noise, which means fail to compare with our proposed method. Our contribution in this stage is developing a new automatic threshold method for extracting spots with high temperatures from a range of spots with different temperatures.

The proposed global threshold method is based on the image histogram, it starts by pre- processing which involves minimizing the background value by analyzing the histogram of input image. First of all, the histogram for the gray image is computed with the number of peaks and valleys (Figure 5.6(a)). Each peak is represented as being in the range 0 to 255(Figure 5.6(b)). Peak and valley detection is computed using local maxima function. We assume that a peak with a high value and away from location 255 represents background. While peaks that near 255 represent the foreground. Peak with less difference from 255 means near 255.In this case, the mean value for all peaks that are near 255 is used as threshold value for binarization process (Figure 5.6(c)).

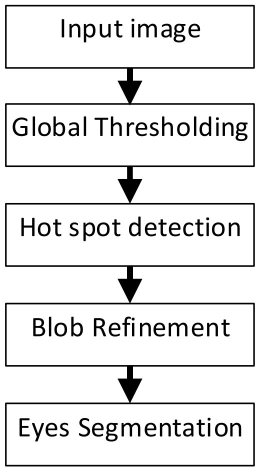
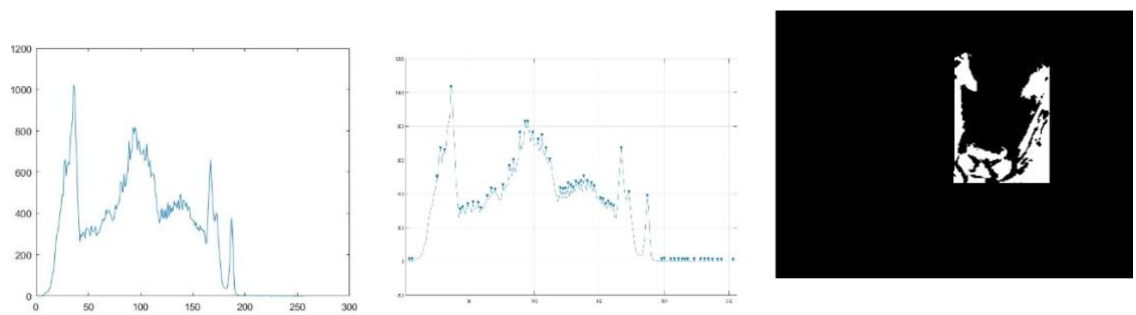


Figure 5. 5: Eye segmentation process

The next task is hot spot detection that includes matrix masking, histogram equalization, binarization and extracting spots with high temperatures. Matrix masking is the result of the multiplication of the binary image with the input image. As shown in Figure 5.6 (d), the region of the image is shown as the black region. This result is processed by histogram equalization. All hot spots will have 255 value, which is used in another binarization step. Afterwards, the binary image is multiplied with the input image. In this stage, we extract all the hot spots of input image. Blob refinement is the result of mean for max temperature for each spot (Figure 5.6 (e)). Eye segmentation represents the spot with the highest temperature in the image (Figure 5.6 (f)). The eye region always belongs to the spot with the high temperature.



(a) (b) (c)

(d) (e) (f)

Figure 5. 6: Eye segmentation :(a) Histogram for image without noise,(b) Identify peak and valley, (c) Global thresholding, (d) Masking, (e) Blob refinement based on hottest spot,(f) Last masking represent eye segmentation.

5.3.4 Eye Localization

The last stage in the proposed method is eye localization. This task has two stages: post-processing and eye detection. Post-processing represents filtering and eliminating the number of candidature spots until the eye region is obtained Figure 5.6(a,b,c). Eye localization includes drawing bounding a box around the eyes showing temperature that is our desired target.

After the deep observation of many infrared thermal images, the eye region is always found have a high temperature compared to the other regions. Extracting eye temperature using infrared thermography images in cattle represents body temperature, and this temperature varies between 36 and 39 Celsius. This range changed from 33 to 34 Celsius when the animal was a short distance from the camera. In this research, this range is adopted to obtain a better performance in proposed eyes detection. In addition, there are two possibilities for the captured infrared thermal image: animal with frontal face or animal with side view showing a single eye. Based on this logical concept, post-processing and eye detection were established. The method for the post-processing is defined Algorithm 5.2:

Algorithm 5.2 Post-processing procedure

1: Read masked infrared image with shown number of regions

2: Obtain max temperature

3: Convert region to binary

4: Obtain centroid and diminution for selected blob

5: Identify search area

```
Masking binary region with input image
if Max(adjacent) – Max(selected blob)
        Convert current entire region to one
        else
        Convert current entire region to zero
end
```

Algorithm starts by processing masked infrared image from previous task. Each region is processed individually to obtain max temperature. The region with the highest max temperature is converted to binary to do more processing. Diminutions that include heights and widths of blob calculated after computing the centroid using the morphology operation. The search region is determined based on the computed diminutions of blob. The equations from 5.3 to 5.6 represent the computation of search region:

$$Rs = i - 2 * D \tag{5.3}$$

$$Re = i + 2 * D \tag{5.4}$$

$$Cs = j - 2 * D \tag{5.5}$$

$$Ce = j + 2 * D \tag{5.6}$$

where Rs and Re denotes the beginning and the end of the search region row. While Cs and Ce refers to column. D refers to the length of selected blob, which represent eye region. The search region (SR) row and column defined as shows in equation 5.7:

$$SR = (Rs: Re, Cs: Ce) \tag{5.7}$$

Finally, j and i mean location of centroid that belong to eye region. Post-processing is necessary to remove undesirable masked regions which are treated as noise (Figure 5.7(a,b,c)).

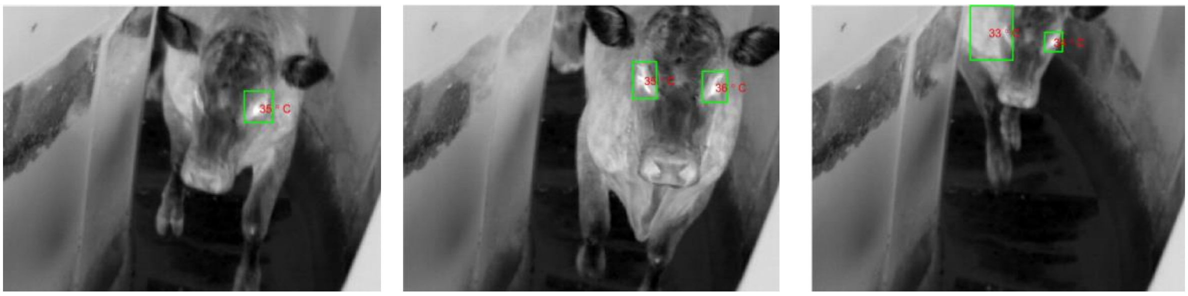
(a) (b) (c)

Figure 5. 7: Post-processing process :(a) obtain dimensions for hottest region ,(b) eye region extraction based on height and width of hottest region, (c)eye localization.

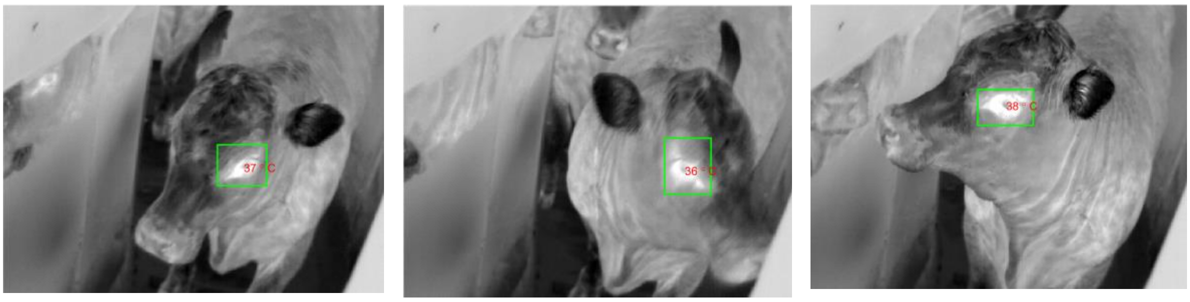
Eye localization will be the last stage of the proposed method and includes a comparison of identified eye region with adjacent region in determined search region (Figure 5.7 (B)). Figure 5.8 shows the results of the eyes detection with identified temperature for cows in different positions and orientations. Temperature measurement is conducted of eye region based on equation (5.8):

$$T_O = T_{min} + \left(\frac{T_{gray}}{T_{mgv}} (T_{max} - T_{min}) \right) \tag{5.8}$$

where T_O is output temperature based on thermal value of eye region, T_{max} and T_{min} refers to maximum and minimum value of temperature in thermal image. T_{gray} represents intensity of pixel in particular point in gray scale thermogram. T_{mgv} is the high intensity value in the gray scale thermogram. The next section discusses the experiment and analysis of the proposed segmentation in comparison with others work.



a b c



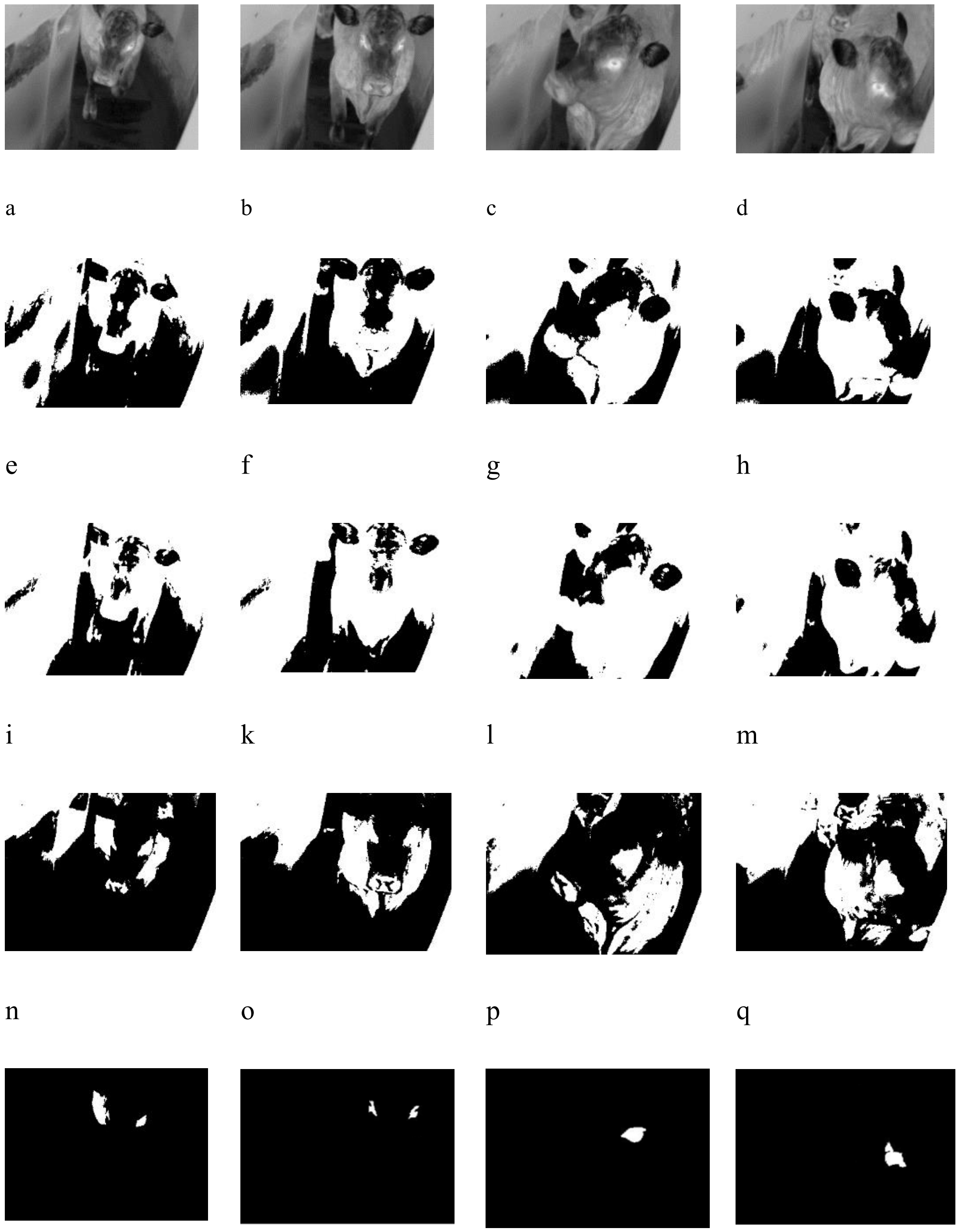
d e f

Figure 5. 8: Eye detection results with showing maximum temperature of eye region:(a) eye detection in frontal view with showing one eye,(b) eye detection in frontal view with showing two eyes, (c) eye detection in far frontal view with showing two eyes, (d) eye detection in side view, (e) blob refinement based on hottest spot,(f) last masking represent eye segmentation.

5.4 Experimental Results and Performance Evaluation

The infrared thermography database used for testing the proposed system was created by converting video to a sequence of frames. The infrared thermal images collection included 700 thermograms covering the complete animal body in different orientations and positions. The captured infrared thermal images were extracted from streaming video at one of slaughterhouse which belong to Sydney University. The background was manipulated in no way, which means that this data is a simulation of the real scenario of animals on a farm. The number of subjects was 35. The images were acquired using AGEMA 590 PAL, ThermaCam S65, A310, T335 with 320 × 240-pixel optical resolution of detectors. The distance between camera and subject was about 3 m. Figure 5.9 (a,b,c,d) demonstrates examples of images from the infrared thermal database. Automatic segmentation methods include Otsu [228] , the fuzzy c-mean method [232]and Maximum entropy [230] used as a benchmark as a result of its widely used in the literature [230].

For performance evaluation, four groups of binary images were created, which involve ground truth, Otus, FCM, Maximum entropy and the proposed method. Ground truth was prepared manually using distinguished software paint.net. All binary images of segmentation methods were prepared automatically using algorithms. The next section shows details of performance evaluation for all segmentation methods.



r s t f

Figure 5. 9: Eye segmentation :(a to d) original images,(e to h) Otus segmentation results, (i to m) FCM segmentation results,, (n to q) Max entropy segmentation results, (r to f)results of proposed segmentation method.

5.4.1 Quantitative analysis

Proposed method evaluated from two sides: ROI localization and eye detection. The performance of the proposed ROIs localization method was assessed using a comparison of the Segmentation Results (SR) and Ground Truth (GT) images as shown in Fig.8. Ground truth (GT) images are the binary images which are prepared by manually segmenting the regions in each image. The Segmentation Results (SR) images include binary images for output of proposed method and competitive methods. Competitive methods involve well-known methods widely used in the literature[233]. These methods are applied on the same image data set. Based on this concept, the author used the following methods for evaluation: Misclassification Error (ME) [146] and F-Measures (FM) [147].

ME refers to the percentage of incorrect classifications between the eye region and background. A lower value of ME means the result of segmentation is better. It can be achieved by testing the overlapping between the segmentation results (RS) and the ground truth (GT). It is defined as in equation 5.9.

$$ME = 1 - \frac{|B_G \cap B_S| + |F_G \cap F_S|}{|B_G \cap F_G|} \tag{5.9}$$

Where B_G and F_G refer to background and foreground of ground truth image. While B_S and F_S belong to segmentation results.

FM measures precision and sensitivity by computing the percentage between recall and precision. A higher value of FM refers to a better result in terms of accuracy. It can be computed with the mathematical equation 5.10.

$$FM = 2 \times \frac{P \times R}{P + R} \tag{5.10}$$

Where P and R refer to precision and recall of segmentation between ground truth and segmentation image. Table 1 shows the list the scores of ME, Sensitivity, Precision and FM tested on 200 infrared images.

Table 5. 1: Results of Segmentation Methods.

Description	Otus	FCM	ME	Proposed Segmentation method
ME	0.6735	0.0690	0.3963	**0.0455**
Sensitivity	0.9007	0.3717	0.5907	**0.9780**
Precision	0.0306	0.0369	0.3044	**0.7212**
FM	0.0590	0.0690	0.1224	**0.8024**

As shown in Table 5.1, the proposed method obtained better results compared to the other methods in terms of ME and FM values. In term of classification error, Otus, FCM, and Maximum Entropy have a lower score compared to the proposed method. The highest error belongs to Otus with value 0.6735, while lower error refers to the proposed method with score 0.0455. In the terms of precision and sensitivity, the highest score belongs to the proposed method with values 0.7212 and 0.9780 respectively. In FM metric which is considered as the percentage between precision and sensitivity, the scores indicate that the proposed method is the best one with value 0.8024. Based on these ME and FM values, proposed method performs well compared to the other methods. However, eye localization is also assessed by applying the methods to each subject individually. The authors used the method utilized by [149] to evaluate the effectiveness of the eye localization. The effectiveness of the proposed method E_D was obtained by dividing the number of images where the eyes were detected correctly N_D by the total number of test images N_A: as in equation 5.11.

$$E_D = \frac{N_D}{N_A} * 100\% \tag{5.11}$$

After analyzing results, it is concluded that the proposed method has the ability to detect eyes correctly with 85%. The false localization occurred as result of a lack of resolution in some thermal images. Moreover, when the animal is far away from the camera, the eye regions become unclear.

5.4.2 Qualitative analysis

The performance of the proposed segmentation method is compared with the most well-known segmentation methods which have been utilized widely in different segmenting types of infrared thermal images. Competitive segmentation methods involve Otsu method [27], Fuzzy C-mean (FCM) [28], and Maximum Entropy [29]. The example results for all segmentation methods are presented in Figure 5.8. As demonstrated in Figure 5.8, the competitive segmentation methods have a lot noise from covering many regions of background. In contrast, the proposed method of segmenting region of interest appropriately compares with ground truth. The results reveal that the proposed segmentation method outperforms the other methods. Furthermore, the proposed method performs well in eye localization with 85% in different orientations and positions.

5.5 Discussion

The proposed method for automatic eye segmentation of thermal images was compared with three other segmentation methods [213, 230, 234]. Up to authors knowledge, no studies have been conducted on automatic eye segmentation in animals, but well-known segmentation algorithms have been used in closely related research studies. Several known studies are not included in this comparison because they are not fully automatic or they are used in visible spectrum[8, 235], or in controlled environment, etc. As shown in Table 5.1, the proposed method is accurate with less error and noise. In addition, outcomes of proposed method indicate the ability for eye region localization in different head poses and when the animal's face is in different positions and orientations (Figure 5.7). An advantage of the proposed method is that it does not require any prepared training sets. In addition, it is easy to implement in indoor situations where the camera can obtain images with appropriate resolution. Unlike the methods mentioned in literature, this method has the ability to detect eyes correctly regardless animal position and orientation toward camera. After eye detection, temperature can be measured and used in further stages for health evaluation.

The proposed method is built based on extracting the hottest spots from the animal body without using a fixed threshold value. The ability to segment the eye region leads to significantly improve eye detection. This method allows researchers to do more processing on particular regions of the infrared image, which enhances their application to systems. The proposed eye detection method can work correctly without scanning the whole image to find features, and it can be applied to detect eyes for multiple animals after identifying the animal face or head. In this case, searching in small region which contain the eyes, leads to the improved speed and accuracy of the classifier, which enhances eye detection for a herd of cattle.

5.6 Conclusion

In this chapter, a new method is proposed for automatic eye segmentation in cattle by utilizing infrared thermal images as data. The contribution of this paper is automatic segmentation and localization for area of interest by localizing the animal body and extracting the eye region from the face through using edge processing, dynamic threshold and thermal intensity. Moreover, this segmentation method is developed with the ability to extract the eye region with less noise in different orientations and positions of target animal. According to the results of this study, the proposed method is effective with the following average 0.0455 and 0.8024 for ME and FM. This means that the proposed method is accurate with less error compared to competitive methods as explained in Table 5.1. In future work, it is intended to use the proposed method to enhance the performance of the eye detection algorithm with higher accuracy rate.

Chapter 6 Stress Evaluation in Cattle

6.1 Introduction

This chapter presents the using of machine learning algorithms in stress evaluation in cattle. Section 6.2 explains the methodology for developing machine learning algorithms for stress evaluation in cattle. Section 6.3 shows the data collection procedure, and Section 6.4 dedicates for cleaning the dataset. In section 6.5, elaborates in detail about selecting features, which are considered the most important block for machine learning, while the following section concentrates more on classification. Afterwards, deep explanation about chosen machine learning algorithms is given by Section 6.6. Section 6.7 discusses the evaluation of several classification algorithms that are used in stress evaluation. Discussion of the result is presented in section 6.6. The chapter culminates with a conclusion in the last section 6.8.

6.2 Methodology

This study adopts the classification methodology for stress detection. In general, a classification methodology can be divided into three main stages as shown in Figure 6.1, which are preparing the dataset, extracting the features from the dataset, and training the model for the later classification task.

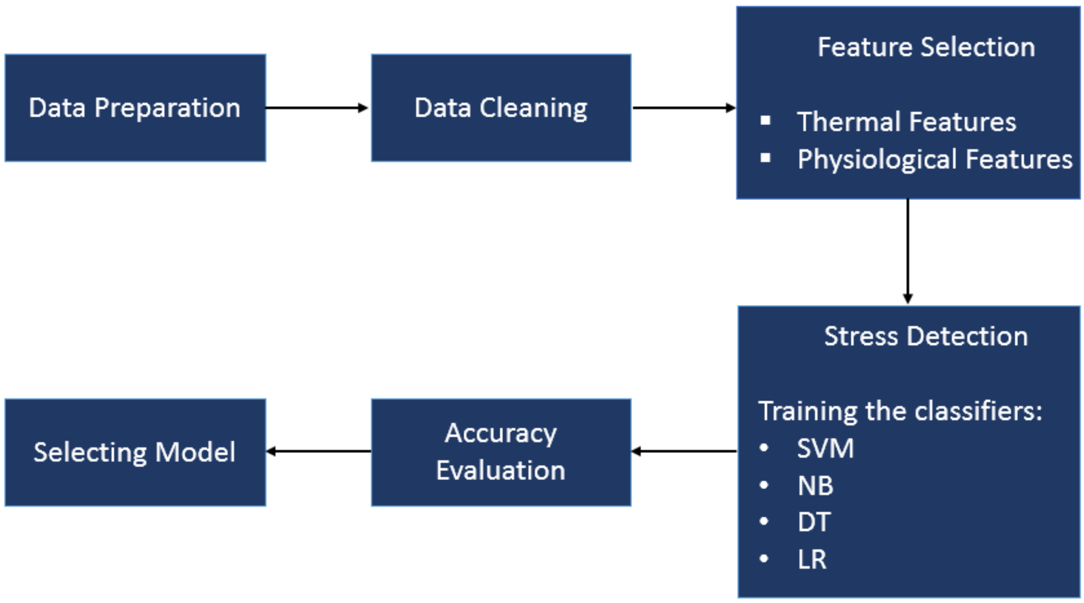


Figure 6. 1: Classification methodology for stress evaluation.

Dataset is prepared through collecting thermal temperature from eyes region as well as physiological data. In data cleaning, any empty record will be removed from dataset. Then, dataset will be labelled to classes based on physiological feature. After labelling and feature selection, Dataset is prepared through collecting thermal temperature from eyes region as well as physiological data. In data cleaning, any empty record will be removed from the dataset. Then, dataset is labelled to classes based on physiological features. After labelling and feature selection, thermal features are used in classification after the training and testing process. In this study, Python programming language is used to build the stress detection models.

6.3 Data Collection

Two types of data were collected: numerical and imaginary data. Numerical data includes measurement of cattle after slaughtering, and temperature data which is acquired from infrared thermal images. The database was collected by technical and medical experts in a commercial abattoir after obtaining ethical approval from Sydney University. The procedure of data collection can be classified into three stages as shown in Figure 6.2. Data collection in stage one and two occurred in a herd of cattle before slaughtering while physiological data in stage three occurred after slaughtering.

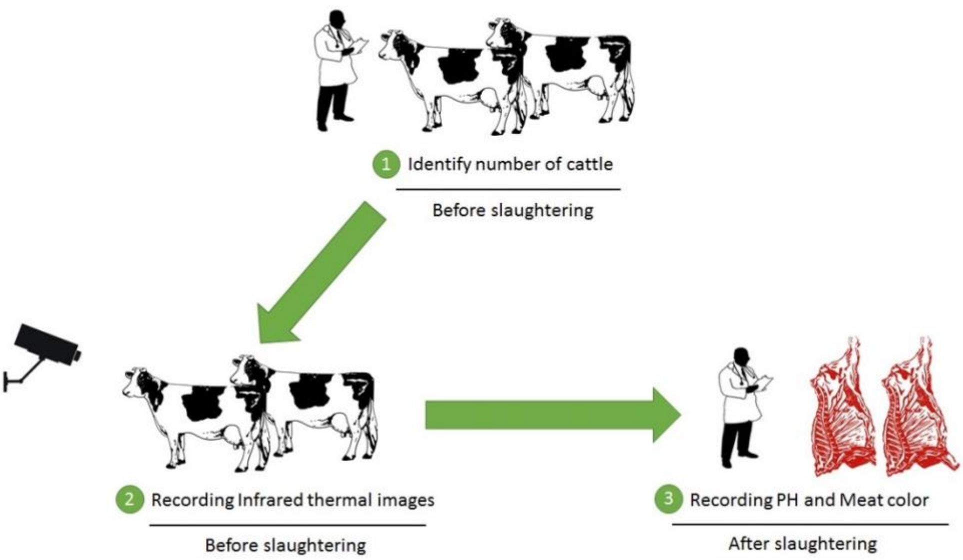
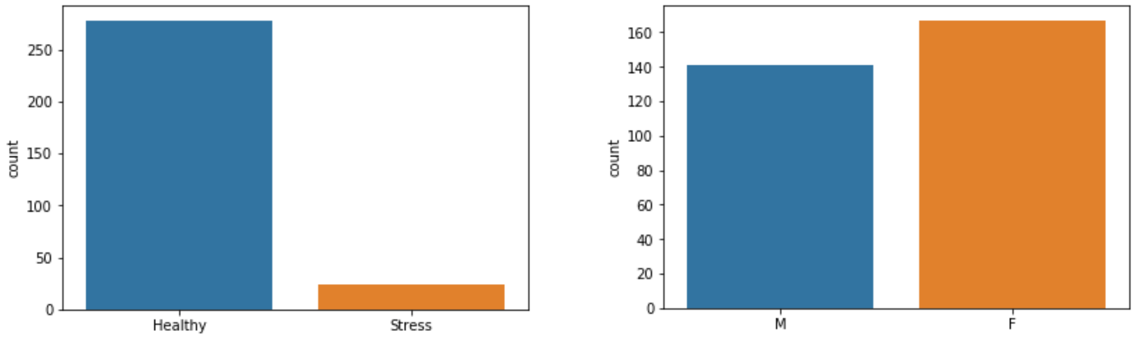


Figure 6. 2: Data collection procedure: stage (1) physiological measurement for cattle before slaughtering, stage (2) temperature measurement using IRT for eye region of cattle before slaughtering, stage (3) PH and meat colour data measurement for cattle carcass after slaughtering.

In stage (1), experts in veterinary medicine identified a number of cattle randomly; in this study 308 head of cattle were selected for this study (Figure 6.2 (1)). The cattle included 167 females and 141 males (Figure 6.2 (b)).



(a) (b)

Figure 6. 3: Subjects data summery: (a) subjects health type, (b) subjects gender.

In stage (2) for the same herd of cattle, infrared thermal images were recorded in order to obtain temperature measurement for eye region for each animal. Details of this stage are explained in the thermal feature section. Stage one and two were conducted with cattle before slaughtering while the last stage of data collection was conducted after slaughtering. In stage (3), PH, meat colour and other physiological data were recorded as the third part of data collection. Based on values of PH and meat colour, collected infrared thermal images were classified into two classes: stressed and healthy cattle. Number of stressed cattle are 24, and number of healthy cattle are 278.

Stage one and three were prepared manually by experts compared to stage two, in which data was collected automatically via eyes segmentation as explained in chapter five. All data were recorded in the abattoir house, which belongs to Sydney University. The circumstances of data capturing were occurred in the indoor environment. Next sections explain each stage in detail.

6.4 Data Cleaning

Data cleaning is in the pre-processing stage, which prepares the dataset for feature extraction and selection. In this stage, all rows of data with missing cells will be removed from dataset.

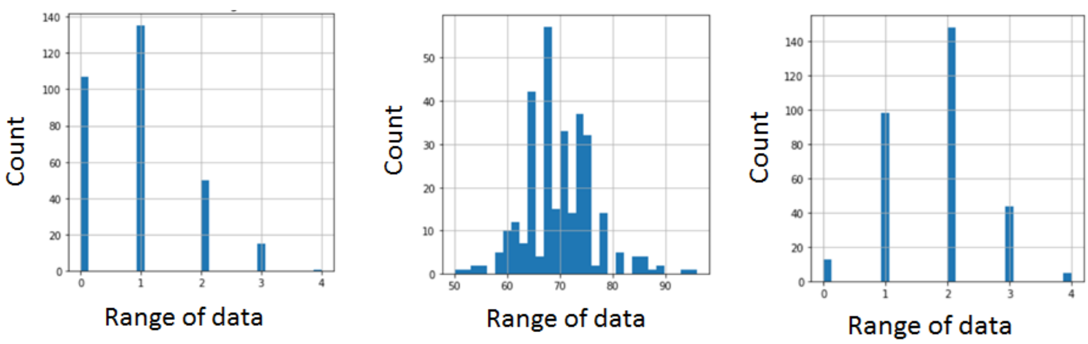
All values of dataset were organized as a table, and each column represents a feature. After cleaning, 300 rows of data remain, which will be used for training and testing of classification methods.

6.5 Feature Selection

After data collection and cleaning, dataset involves several features include thermal and physiological features. Physiological features involve PH, meat colour and other data. Based on PH and meat colour, thermal features split into two classes: healthy and stressed. Next subsections explain in detail these kinds of features.

6.5.1 Physiological Features

After slaughtering, veterinary medical experts examined the carcasses of 308 of cattle. After medical examination, several physiological data collected from cattle carcass in order to test meat quality. These physiological data include carcass weight, size of muscle, amount of fat within muscle, meat colour, fat colour, depth of far under the skin in millimetre, and PH. All previous researches confirm that value of meat colour and PH lead to judge whether meat is dark or fresh. Higher PH is worse meat quality, which mean PH above 5.7 lead to dark meat, and animal was suffered from stress pre-slaughter. Meat colour is another indication for meat quality and stress for cattle. Meat colour with value above 4 means dark meat and cattle was under stress before slaughtering. Figure 6.4 shows the data distribution for each single feature.



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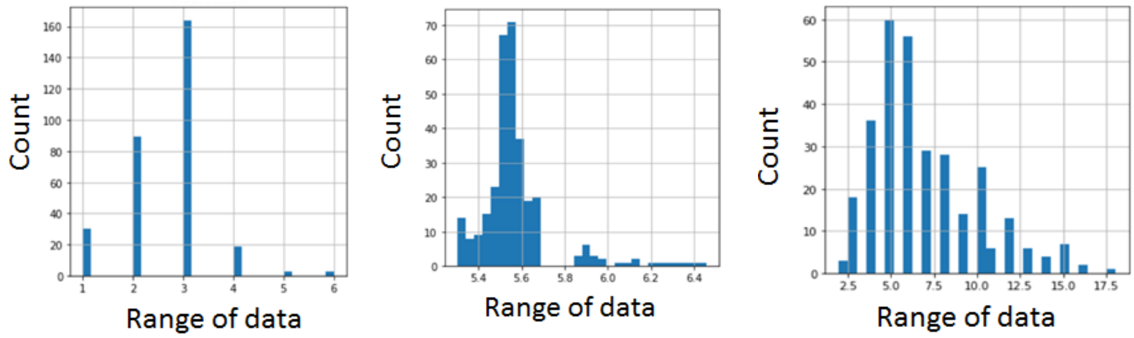

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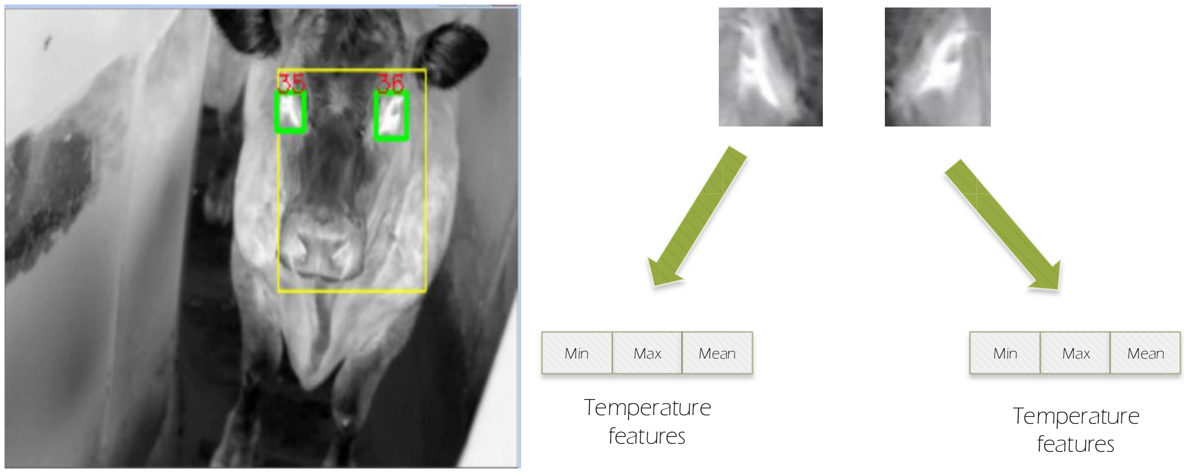
Figure 6. 4: Data distribution of physiological features: (a) Histogram distribution for fat of muscles, (b) Histogram distribution for size of muscles, (c) Histogram distribution for fat colour, (d) Histogram distribution for meat colour, (d) Histogram distribution for meat colour, (e) Histogram distribution for PH, (f) Histogram distribution for rib fat.

As shown in Figure 6.4, the first feature is the amount of fat within the muscle in the range 0 to 4, which mean 4 high fat (Figure 6.4 (a)). Another feature is the size of the muscle on the back of the animal, which is called the rib eye muscle (Figure 6.4 (b)). The range of values of this feature are between 50 to 90. Fat colour is in the range 0 to 4, and this range reflects the degree of meat quality (Figure 6.4(c)). Another important feature is meat colour, which is in the range 1 to 6 (Figure 6.4(d)). In this feature, any value above 4 means dark meat and slaughtered animal was under stress. Values less than 4 mean meat is good quality, and animal is healthy before slaughtering. Another feature that indicates stress in cattle is PH. PH values in range 1 to 6.5, and above 5.7 means dark meat and slaughtered animal was under stress. PH below 5.7 means meat with good quality and healthy cattle. Last feature is rib fat that shows the amount of fat on the ribs.

6.5.2 Thermal Features

Temperature values using IRT are extracted from eye region and used as features to detect stress in cattle. These features involve maximum, minimum, mean temperature for 308 subjects. In order to extract temperature features from thermal images, face detection was performed on infrared thermal images as explained in chapter four. Afterwards, eye segmentation is performed for identifying eye region as explained in chapter five. As shown in Figure 6.5, face detection used for identifying ROI, and eye segmentation used for extracting thermal features.



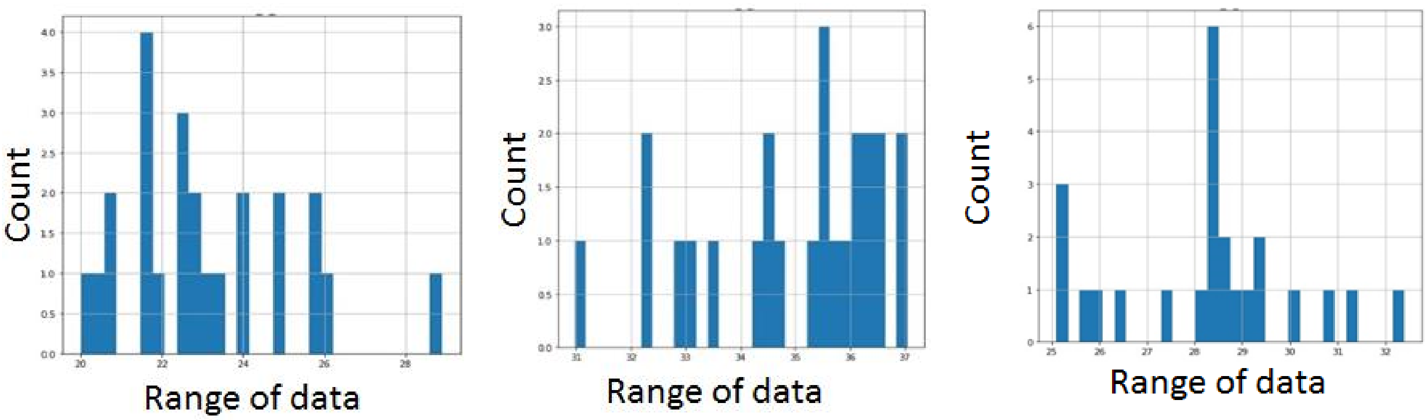
(a) (b)

Figure 6. 5: Procedure for thermal features extraction: (a) face detection and eye segmentation, (b) temperature features extraction from eye region.

Temperature values are labelled to animal under stress and healthy. Labelling thermal features to two classes is conducted based on PH and meat colour values. In stressed class, infrared thermal features are grouped for cattle with PH above 5.7, and meat colour above 4. In healthy class, another infrared thermal feature is prepared as set for cattle with PH less than 5.7 and meat colour less than 4. Next subsection shows data distribution of temperature for healthy and stressed cattle.

6.5.2.1 Thermal features for stressed cattle

Figure 6.6 illustrate the data distribution of temperature values for 24 stressed cattle.



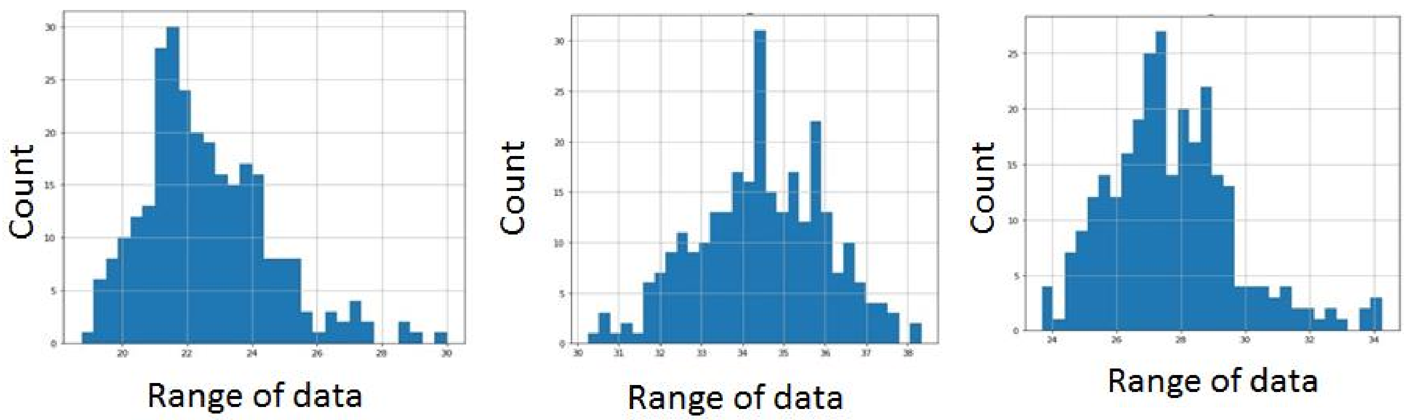
(a) (b) (c)

Figure 6. 6: Data distribution of temperature values for stressed cattle: (a) histogram distribution for mean of minimum temperature, (b) histogram distribution for mean of maximum temperature, (c) histogram distribution for mean of mean temperature.

As shown in Figure 6.6 above, range of minimum temperature between 20 to 28, and highest frequent temperature value between 20 and 22. The less frequent value is more than 28. For maximum temperature distribution, temperature range between 31 to 37 refers to most frequent value of maximum temperature. Highest peak is values between 35 and 36, and lowest peak is 31. Last histogram distribution is as shown in Figure 6.5(c), range of temperature values for mean temperature between 25 and 32. Peaks indicates that range between 28 and 29 is the highest heights and lowest values are less than 32.

6.5.2.2 Thermal features for healthy cattle

Figure 6.7 demonstrate the histogram data distribution of temperature values for 278 healthy cattle.



(a) (b) (c)

Figure 6. 7: Data distribution of temperature values for stressed cattle: (a) histogram distribution for mean of minimum temperature, (b) histogram distribution for mean of maximum temperature, (c) histogram distribution for mean of mean temperature.

As shown in Figure 6.7 above, range of minimum temperature between15 to 30, and heights frequent temperature value between 20 and 22. While less frequent value is 30. For maximum temperature distribution, temperature range between 30 to 38 refers to most frequent value of maximum temperature. Heights peak is values between 35 and 34, and lowest peak is 30. Last histogram distribution as shown in Figure 6.7(c), range of temperature values for mean temperature between 24 and 34. Peaks indicates that range between 26 and 28 is the heights and lowest values that less than 24. In the next section, several classification algorithms are used to detect stress among a number of cattle.

6.6 Machine Learning Algorithms

Experiments are conducted on datasets by using four well-known machine learning algorithms, which include: Support Vector Machines (SVM), Naïve Bayes (NB), Decision Trees (DT), and Logistic Regression (LR). In these algorithms, four classifiers will be created for identifying stressed cattle from healthy cattle. This task is called classification, which is performed by machine learning algorithms. The literature has shown that these algorithms have proven to give high accuracy results.

6.6.1 Support Vector Machines (SVM)

A Support Vector Machine is a supervised machine learning type that uses hyperplane or a set of hyperplanes to separate classes. During training data, several numbers of hyperplanes are drawn as well as distance between hyperplanes and data's class till reaching the optimal hyperplane. The outcome of trained SVM algorithm is optimal hyperplane, which has the ability to categorize new input data. An optimal separation is achieved through the hyperplane as well as the largest distance to the closest data point of any class. In this case, generalization error of the classification is reduced when the distance is larger. The formula is shown in Equation 6.1.

$$W \, . \, X + b = 0 \qquad (6.1)$$

where w is a weight vector, x is input vector, and b is bias.

6.6.2 Naïve Bayes (NB)

Naïve Bayes can be defined as a probability model, which works based on Bayes' Theorem. The concepts behind this NB is several hypotheses assume with finding the variables and its effect on others. This algorithm is suitable when data has features with high dimensions. The Naïve Bayes algorithm is used widely in different applications such as in medical diagnosis. The Naïve Bayes can be conducted using the formula that is shown in Equation 6. 2.

$$P(C_k \backslash x) = \frac{P(C_k)P(x \backslash C_k)}{P(x)} \qquad (6.2)$$

P(c\x) is the posterior probability of class, c means class, x refers to attributes. P(c) is the pre-probability of class. P(x\c) is the likelihood which is the probability of predictor given class.
P(x) is the prior probability of predictor.

6.6.3 Decision Tree (DT)

Decision Tree algorithm is a supervised learning type, which is used in two problems types: classification and regression. The concept behind its work is to create a tree diagram that involves several classification models and then splits the dataset into a smaller partial dataset and then prepares the tree of decisions gradually in the next stages. The outcome of this algorithm is a tree, with decision branches. Afterwards, using the provided information in the head of tree, and progress is made down to each branch until classification is achieved. Each input feature is divided among branches and similarity among features is made. It can be achieved though using the following equation, where J means classes and P means items:

$$IG(P) = 1 - \sum_{i=1}^{j} P_i^2 \tag{6.3}$$

6.6.4 Logistic Regression (LR)

Logistic regression (LR) is a well-known machine learning algorithm that is used widely for the classification task. In binary classification task, LR algorithm uses data to fit the logistic function. Logistic function $h_\theta(x)$ takes values in the range “0” to “1”. Logistic function computes by using equation (6.4):

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}} \tag{6.4}$$

Logistic function represents the probability of input feature vector belonging to a certain class. In equation (6.4), x refers to vector feature. θ is a vector of n+1 parameter which are formulated by training.

6.7 Results

Dataset classifies into two classes: healthy and stressed cattle. It contained temperature features for eyes region. These features used data cleaning that is implemented in order to remove empty records and prepare a solid dataset for classification. The dataset has two classes: healthy and stressed. Binary classification is applied in this study.

For seeking efficiency and accuracy, accuracy, sensitivity, precision and F-measure are used as evaluation metrics for testing performance. The dataset is split to 80% for training and 20% is left for testing. Next section shows the results and analysis for the following algorithms: Logistic

Regression (LR), Decision Tree Classifier (CART), Naive Bayes (NB) and Support Vector Machine (SVM).

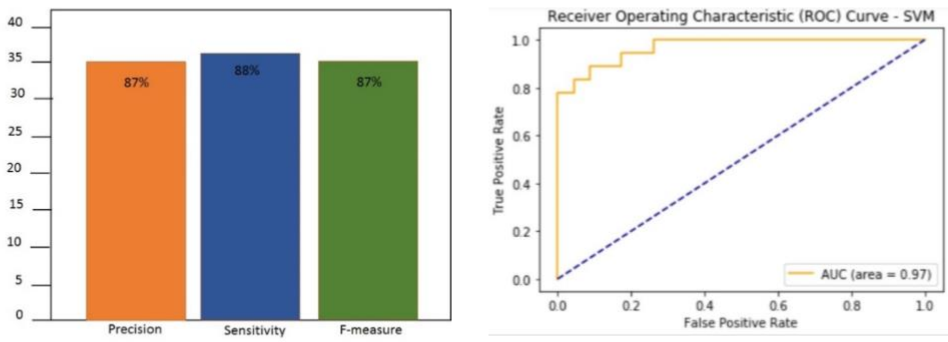
6.7.1 Support Vector Machine Results

Table 6.1 shows results of Support Vector Machine in detecting stressed and healthy cattle. The performance is measured using accuracy, precision, recall, and F-measure.

Table 6. 1: Stress classification using SVM.

Class	Precision	Sensitivity	F-measure	Accuracy	AUC
Healthy	0.89	0.89	0.89	0.90	0.97
Stress	0.91	0.91	0.91		
Total	0.90	0.90	0.90		

As shown in Table 6.1, SVM has the ability to detect stress class with the precision of 0.91, F-measure of 0.91 and recall of 0.91. In healthy class for SVM, the precision of 0.89, F-measure of 0.89 and recall of 0.89. In detecting both classes, the general accuracy is 0.90, the precision of 0.90, F-measure is 0.90 and recall is 0.90. Result visualization for evaluation metrics is shown in Figure 6.8 below.



a b

Figure 6. 8: Results visualization for stress classification using SVM: (a) Result visualisation for Precision, Sensitivity, F-measure, (b) ROC curve and AUC for SVM results.

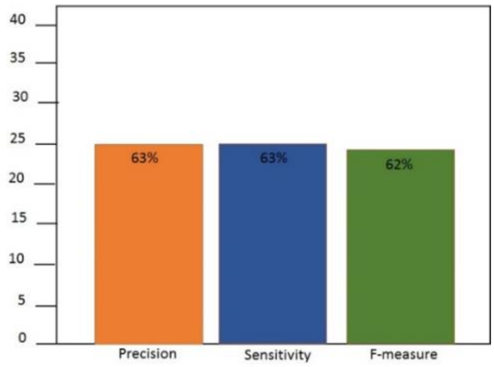
6.7.2 Naïve Bayes Results

Table 6.2 shows results of Naïve Bayes in detecting stressed and healthy cattle. The performance is measured using accuracy, precision, recall, and F-measure.

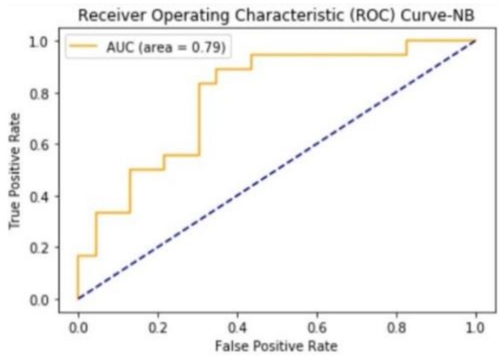
Table 6. 2: Stress classification using Naïve Bayes

Class	Precision	Sensitivity	F-measure	Accuracy	AUC
Healthy	0.59	0.56	0.57	0.63	0.79
Stress	0.67	0.70	0.68		
Total	0.63	0.63	0.62		

As shown in Table 6.2, Naïve Bayes has the ability to detect stressed class with accuracy of 0.63, the precision of 0.67, F-measure of 0.68 and recall of 0.70, while in healthy class for Naïve Bayes, the accuracy is 0.63, the precision is 0.59, F-measure is 0.57 and recall is 0.56. In detecting both classes, the evaluation metrics show, for accuracy of 0.63, the precision of 0.63, F-measure of 0.62 and recall of 0.63. Result visualization for evaluation metrics is shown in Figure 6.9 below.



a



b

Figure 6. 9: Results visualization for stress classification using Naïve Bayes: (a) Result visualisation for Precision, Sensitivity, F-measure, (b) ROC curve and AUC for Naïve Bayes results.

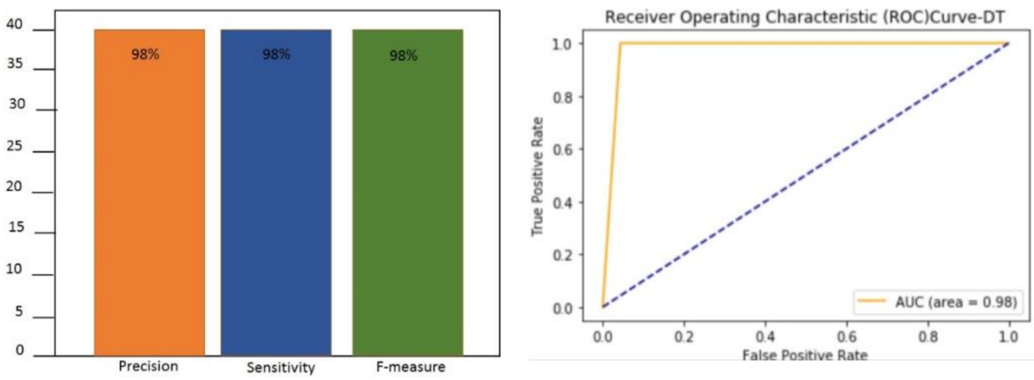
6.7.3 Decision Tree Results

Table 6.3 shows results of Decision Tree in detecting stressed and health cattle. The performance is measured using accuracy, precision, recall, and F-measure.

Table 6. 3: Stress classification using Decision Tree

Class	Precision	Sensitivity	F-measure	Accuracy	AUC
Healthy	0.95	1.00	0.97	0.98	0.98
Stress	1.00	0.96	0.98		
Total	0.98	0.98	0.98		

As shown in Table 6.3, Decision Tree has the ability to detect stressed class with accuracy of 0.98, the precision of 1.0, F-measure of 0.98 and recall of 0.96, while in healthy class for Decision Tree, the accuracy is 0.98, the precision is 0.95, F-measure is 0.97 and recall is 1.0. In detecting both classes, the evaluation metrics for accuracy of 0.98, the precision of 0.98, F-measure of 0.98 and recall of 0.98. Result visualization for evaluation metrics are shown in Figure 6.10 below.



a b

Figure 6. 10: Result visualisation for Stress classification using Decision Tree: (a) Result visualisation for Precision, Sensitivity, F-measure, (b) ROC curve and AUC for Decision Tree results.

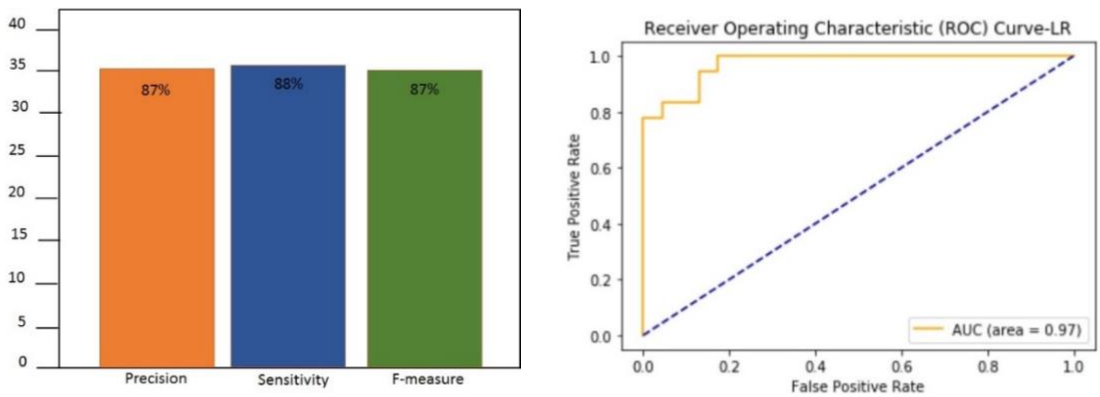
6.7.4 Logistic Regression Results

Table 6. 4 shows results of Logistic Regression in detecting stressed and healthy cattle. The performance is measured using accuracy, precision, recall, and F-measure.

Table 6. 4: Stress classification using Logistic Regression.

Class	Precision	Sensitivity	F-measure	Accuracy	AUC
Healthy	0.84	0.89	0.86	0.88	0.97
Stress	0.91	0.87	0.89		
Total	0.87	0.88	0.87		

As shown in Table 6.4, Logistic Regression has the ability to detect stress class with accuracy of 0.88, the precision of 0.91, F-measure of 0.89 and recall of 0.87. In the healthy class for Logistic Regression, the results show the accuracy of 0.88, the precision of 0.84, F-measure of 0.86 and recall of 0.84. In detecting both classes, the evaluation metrics for accuracy of 0.88, the precision of 0.87, F-measure of 0.87 and recall of 0.88. Result visualization for evaluation metrics shows in Figure 6.11 below.



a b

Figure 6. 11: Results visualization for stress classification using Logistic Regression: (a) Result visualisation for Precision, Sensitivity, F-measure, (b) ROC curve and AUC for Logistic Regression results.

6.8 Discussion

The main aim of this research is developing a system for stress detection in cattle. With this goal, we use physiological features of cattle body to identify classes of data set. By using Ph and meat colour, dataset is categorized into two classes: healthy and stressed. Dataset includes thermal features of eye region: mean, maximum and minimum temperature for eyes region.

With 80% training and 20% testing, as shown in Table 6.5, Decision Tree is more accurate with value 98% from Logistic Regression, Naïve Bayes and Support Vector Machine.

Table 6. 5: Stress classification summery

Evaluation	LR	SVM	NB	DT
Accuracy	0.88	0.88	0.63	0.98
Specificity	0.87	0.87	0.63	0.98
Sensitivity	0.88	0.88	0.62	0.98
F-measure	0.87	0.87	0.62	0.98
AUC	0.97	0.97	0.79	0.98

These results include using other evaluation metrics: Specificity Sensitivity and F-measure. Specificity calculates the true negatives that were also predicted as negative. Sensitivity refers to the true positives that were also classified as positives. F-measure is the percentage between Specificity and Sensitivity. In term of Specificity, highest value 98% belongs to DT, and lowest 63% refers to NB. SVM and LR have the same value, 0.87. In Sensitivity, DT achieves better performance with value 98%. Also, LR and SVM perform well but with value 88%. Less value belongs to NB with value 0.62. In last evaluation, F-measure, classification algorithms including DT are accurate with value 98%, while LR and SVM are 87%, and the lowest value is 0.62 for NB. In this new study, four machine learning algorithms are used in a new dataset. The results show the best classifier is Decision tree, and the worst one is Naïve Bayes.

6.9 Conclusion

This chapter presents the details of the stress detection in cattle. In stress detection, dataset is collected, which is then organized in three stages. Two stages before cattle slaughtering and one dataset is collected after slaughtering. From the dataset, features classify to physiological and thermal features. Four linear classification algorithms were used for stress classification, which include: Support Vector Machine, Naïve Bayes, Decision Tree and Logistic Regression. Based on results analysis, Decision Tree is the best for stress detection with an average of 98% for accuracy, precision, sensitivity, F-measure and AUC. Results are visualized using percentage and ROC curve.

Chapter 7 Conclusion and Future works

7.1 Thesis Summary

This study proposes a new system based on utilization machine learning, image processing and computer vision to detect stress in cattle pre-slaughtering, which will enhance meat production globally by preventing dark meat problem in cattle post-slaughtering. In the proposed system, machine learning is used for stress detection after obtaining temperature from the eyes region in cattle. Image processing is used to develop a new method for eyes segmentation in cattle. Eye segmentation could not be achieved without locating the face region, which is located through using computer vision.

In order to propose a system for stress detection in cattle, this research focused on two important perspectives. Firstly, an intensive investigation is conducted about previous studies regarding the stress problem in cattle and its a negative role in creating dark meat. This direction includes details about stress, the factors that cause stress, the currently used methods for detecting stress before slaughtering, and the negative impacts of stress in cattle. Negative effects of stress involve dark meat, feedlot and milk production. Currently used methods for detecting stress in cattle pre-slaughtering include obtaining temperature from eyes region through locating eyes region manually in the infrared thermal image. Secondly, this study involves deep investigation about previous studies regarding using infrared thermography for developing an automated system. In addition, components of an automated system are investigated and explained in details of each single component. Components of an automated system include pre-processing, segmentation, feature extraction and classification. As examples of automated systems that are studied extensively are fever, infection and stress detection in humans. In the fever detection case, the components of this kind of automated system include eye and face detection. In addition, canthus segmentation of eye region, which used for obtaining temperature is studied. Captured temperature of canthus region is used for detecting fever. An automated system for infection and stress detection involves face detection, eye segmentation with obtaining temperature from eyes region and uses these temperatures as feature to train a machine learning algorithm. Afterwards, trained machine learning algorithm will be used for stress and infection detection.

After deep studying of the main components of these automated systems, the author finds out the main components of the proposed system. Proposed system involves face detection, eye segmentation and machine learning for classification task. Previous studies that were related with eye segmentation, face detection and machine learning were reviewed extensively. This reviewing involves methodologies and implementations of eye segmentation, face detection and used machine learning algorithms in different medical applications. In addition, reviewing of different metrics that were used for examining performance was carried out.

In point of fact, using the proposed system could help the meat production industry by reducing the need for a medical expert's assessment. This type of approach is able to assist the specialist in veterinary to improve their decision-making process. This research was inspired by the urgent need for developing an automated system for stress detection, which led to preventing dark meat. In fact, the use of the proposed system as a diagnostic tool could reduce the need for specialist assessment as the system can learn from previously diagnosed cattle to diagnose new cases.

After proposing the main components of the stress detection system, each component is studied and investigated deeply with examining performance. First component is Multi-view face detection in cattle. In this part, a new method was proposed to detect cattle's face in different view and orientation of cattle's body. Performance was examined based on the results of proposed method compared to results of ground truth, which was prepared manually.

Second component of proposed system is eyes segmentation. In this second component of proposed system, image with detected of face used as input for eye segmentation method. After face detection, a new method is proposed for identifying eye region automatically with shown temperature of this region. Performance of eye segmentation method was assisted by comparison between manual segmentation and the result of automatic segmentation. In addition, proposed method for eye segmentation was compared with other automatic eye segmentation methods. Results were shown that proposed method performed well compared to others.

Last component of proposed system is stress detection. In this part, temperatures obtained from segmented eye region, and captured temperature for each cattle were arranged as three groups: minimum, mean and maximum temperature. These groups with physiological data were arranged as features, which were used in a training machine learning algorithm. Machine Learning models (ML) are considered to be a powerful technique in the field of scientific research that enables computers to learn from data [236]. Features were labelled to two classes, stressed and healthy. After labelling, features were used to train a number of machine learning algorithms for classification including the Artificial Neural Network, the Random Forest model, and the Support Vector Machine. After training, a part of the dataset was used to test trained classification algorithms. According to results, trained classification algorithms perform well in detecting stress in cattle. In this case, the last component was achieved. Our proposed system addressed the issues with chapter 2 as there is no sufficient system to deal with stress in cattle. It resolved the dark meat issue through detecting stress automatically.

7.2 Research Contributions

The thesis is commenced with providing the medical background about the stress issue in cattle and current used of conventional methods for stress diagnosis in order to set some foundations for the automated diagnostic system. Afterwards, a detailed review and analysis are provided for the existing studies presented in the literature for the development of automated diagnostic systems for fever, infection and stress in humans using Infrared Thermography. Based on previous studies, the research gap is addressed, which referred to there being no automated system for detecting stress in cattle. In order to achieve an automated system for detecting stress in cattle, three research objectives were identified as were mentioned in chapter one: multi-face detection, automatic eye segmentation and stress detection.

The first contribution of the thesis in the detection phase is the development of a novel method for multi-view face detection in cattle using an infrared thermal dataset. This proposed method used three classifiers with minimizing false detection through using temperature thresholding. The proposed method achieved an average True Detection Rate of around 90%, 99% for precision, 91% sensitivity, 95% for f-score. These results show that the proposed method for multi view face detection has a highly improved performance compared to current used method in the area for this application.

The second contribution of this thesis in the segmentation phase is the development of a novel method for automatic eye segmentation in cattle. In this stage, a new method was proposed for thresholding and noise elimination. This proposed segmentation method was conducted on the detected face region. The proposed method achieved a high average in terms of precision, sensitivity, and f-score with less average in term of misclassification. Proposed segmentation method was compared with three well-known automatic segmentation methods, Fuzzy K-mean clustering, Otus and entropy, and results are shown that the proposed method for automatic eyes segmentation has a highly improved performance compared to current used methods in the segmentation field.

The last contribution of this thesis in the automation phase is the development of a novel method for automatic stress detection in cattle. In this last stage of the proposed system, a real dataset was collected at the abattoir in Sydney. Dataset includes thermal temperature of eyes region with physiological data of 308 of cattle. After preparing the dataset for machine learning, thermal temperature with physiological data for 300 of cattle was used. Afterwards, the dataset was labelled to two classes: healthy and stressed. Due to the dataset having two classes only, linear classification algorithms were used in this study. In order to find the best classifiers that can yield the best accuracy and performance, this study selected a number of algorithms as shown in chapter 6. In terms of Accuracy, Specificity, Sensitivity and F-score, results show that Support Vector Machine, Logistic Regression, Random Forest Classifier, Linear Discriminant Analysis, and K Neighbours Classifier perform well compared to others. More details about methodology for stress detection is explained in chapter six. After achieving research contributions, main contribution was achieved, which is developing a system for stress detection in cattle.

This study is new with all contributions, and there is no one done any single study or research about using infrared thermography in cattle in the fields using computer vision, image processing and machine learning. Firstly, Multi-view face detection is a new study and contribution to field computer vison, which used multi-view face detection in cattle using infrared thermography. In addition, automatic eye segmentation in cattle using infrared thermography is a new study and this study is a contribution to field image processing. Lastly, stress detection using machine learning is a new study and this study is a contribution to machine learning and automation field through using thermal temperature of eyes region as features to develop a number of classification algorithms.

7.3 Conclusion and Future Research

With the success of our experimental study, this study considers further work directions, including improvements to the proposed system for stress detection in cattle and extending its proposed techniques. In this thesis, the farm in Sydney in Australia has supported this research with data of 308 cattle for medical purposes. These data include infrared thermal images for cattle before slaughtering and physiological data such as Ph and meat colour for the same number of cattle after slaughtering. Further research is recommended to make confirmation on our findings, where a large number of data could be used also to advance the performance of the results. In this section, I emphasize the possible extensions to medical applications as discussed below.

- This study considers for future work the use of the infrared thermal image for detecting other parts of cattle's bodies such as mouth, nose and legs. Rising temperature in these parts give indication of inflammation and infections in cattle. It is required in this future direction to develop detection and segmentation methods, which could be considered as another future contribution to two fields: computer vision and image processing.
- Another future direction for this research is to use a deep learning technique. Deep learning is an important part of the machine learning field. With using deep learning, the features extraction and selection are selected automatically. Using deep learning to extend this research requires preparing a very large amount of data which could reach to hundreds of thousands of animals.
- The proposed system for stress detection in cattle can be extended by using sensors for obtaining weather temperature and humidity. Using these sensors with adopting Internet Of Things (IOT) techniques and infrared thermal camera could improve the performance of the proposed system significantly.
- The dataset could be extended through adding other types of data such as heart rate and respiration as well as thermal temperature. This can make our system more robust and can be used with any type of illness in cattle.

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