

**ANALYSIS OF FEATURE REDUCTION
ALGORITHMS TO ESTIMATE HUMAN STRESS
CONDITIONS**

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**ANALYSIS OF FEATURE REDUCTION
ALGORITHMS TO ESTIMATE
HUMAN STRESS CONDITIONS**

by

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LIST OF ABBREVIATIONS

GMFM	Google Mesh Face Model
ROI	Region of interest
IPS	Institut Pengajian Siswazah
USM	Universiti Sains Malaysia
PCA	Principal Component Analysis
ANOVA	Analysis of Variance
SVM	Support Vector Machine
DT	Decision Tree
LR	Logistic Regression
GA	Genetic Algorithm

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ANALISIS ALGORITMA PENGURANGAN CIRI UNTUK MENGANGGAR KEADAAN STRES MANUSIA

ABSTRAK

Tekanan adalah tindak balas normal organisma manusia yang dicetuskan dalam situasi yang memerlukan tahap pengaktifan tertentu. Reaksi ini mempunyai kesan positif dan negatif terhadap kehidupan setiap orang. Pengimejan berasaskan terma telah menunjukkan hasil yang menjanjikan dalam mengesan tekanan secara tidak bersentuhan dan tidak invasif. Oleh itu, kajian ini bertujuan untuk membentangkan analisis prestasi pengelasan ciri apabila digabungkan dengan algoritma pemilihan ciri untuk menganggar tekanan manusia berdasarkan ciri muka pengimejan terma. Tiga pengelas hibrid, Mesin Vektor Sokongan (SVM), Pokok Keputusan (DT) dan Regresi Logistik (LR) digabungkan dengan analisis pengurangan ciri, Analisis Komponen Utama (PCA) dan Analisis Varians (ANOVA) telah dinilai dengan pengesahan 10 kali ganda untuk mengira ketepatan klasifikasi. Empat ciri statistik telah diekstrak; min, maksimum, minimum dan sisihan piawai nilai skala kelabu daripada enam kawasan kawasan yang diminati. Keputusan menunjukkan bahawa pengelas hibrid DT-ANOVA mencapai ketepatan yang lebih tinggi sebanyak 62% berbanding yang lain 90 pengelas gabungan. Penemuan menunjukkan bahawa DT-ANOVA berprestasi baik dengan set data kecil, manakala SVM dan LR boleh meningkatkan ketepatan apabila digabungkan dengan ANOVA untuk set data yang besar. Penemuan juga mencadangkan bahawa ANOVA boleh memberikan prestasi yang setanding dengan PCA. Kawasan kawasan antara bibir bawah dan dagu menyumbang paling banyak kepada klasifikasi. Ciri statistik maksimum dan minimum bagi wilayah yang disebutkan memberikan signifikan yang bermakna untuk anggaran

tekanan. Akhir sekali, dapatan menunjukkan bahawa suhu positif dan negatif boleh ditentukan.

ANALYSIS OF FEATURE REDUCTION ALGORITHMS TO ESTIMATE HUMAN STRESS CONDITIONS

ABSTRACT

Stress is a normal reaction of the human organism which triggered in situations that require a certain level of activation. This reaction has both positive and negative effects on everyone's life. Thermal-based imaging has shown promising results in detecting stress in a non-contact and non-invasive manner. Therefore, this study aimed to present analyse of the performance of feature classify when combining with feature selection algorithm to estimate human stress based on the facial feature of thermal imaging. Three hybrid classifiers, Support Vector Machine (SVM), Decision Tree (DT) and Logistic Regression (LR) combined with feature reduction analysis, Principal Component Analyse (PCA) and Analysis of Variance (ANOVA) was evaluated with 10-fold validation to compute classification accuracy. Four statistical features was extracted; mean, maximum, minimum and standard deviation of the gray scale value from six area regions of interest. Results showing that hybrid classifier DT-ANOVA achieves higher accuracy of 62% compared to others 90 combination classifiers. The findings demonstrated that DT-ANOVA performs well with a small dataset, while SVM and LR can improve the accuracy when fused with ANOVA for a big dataset. The findings also suggested that ANOVA can provides comparable performance as PCA. Region of area between lower lip and chin contributed most to the classification. Maximum and minimum statistical features of the mentioned region provide meaningful significant for stress estimation. Lastly, the findings shows that temperature of the positive and negative can be determined.

CHAPTER 1

INTRODUCTION

1.1 Background

The word “stress” defined in many contexts. An inclusive definition of stress refers to the biological response to a physiological or psychological stimulus (Lederbogen, et al., 2014). The reaction produced by the human body towards a pressurized environment is triggered by stress. The human brain coordinates an instant body preparation to face the pressurized environment, called stress. Based on the oxford dictionary, the term stress is referred to the mental pressure caused by the problems in individual life (Manousos, et al., 2014). Cambridge dictionary defined stress as the great worry caused by a difficult situation, or something that causes this condition (Dinges, et al., 2005). McDuff et al. (2016) interprets the stress term as the sum of the non-specific response of the body to any demand (Selye, 1976).

Confusion in determining whether stress was a stimulus as defined in physics or response as used by H.Selye (1976) has afflicted the stress literature. The term stress used in Selye’s work tradition refers to a response, whereas in its original usage, within the science of physics, it referred to a stimulus, and the term strain referred to the response. To be consistent with Selye's original notation, the term stress is referred to a physiological reaction or response. The term stressor refers to the stimulus that triggers the stress response. There are two primary forms of stressors: psychological stress (including personality-based stressors) and biogenic stressors. Psychological stressors are the stressor caused by the cognitive interpretation of the event.

The meaning of the event is dependent on how the event is interpreted. Biological (or biogenic) stressors are biological changes in a body that trigger a physiological response. They cause physiological arousal without the involvement of cognitive interpretation. After understanding the stress and stressors, the research introduced the working definition for stress in human stress literature: Stress is a physiological response that serves as a mechanism of mediation linking any given stressor to its target-organ effect or arousal.

Selye (1975) differentiates constructive from destructive stress, proving that not all stress is detrimental. He named the positive stress ‘eustress’ which acts as a motivate force to improve the life quality. The opposite stress is called distress stress. Selye also defined the relationship between stress and health performance as shown in Figure 1.1.

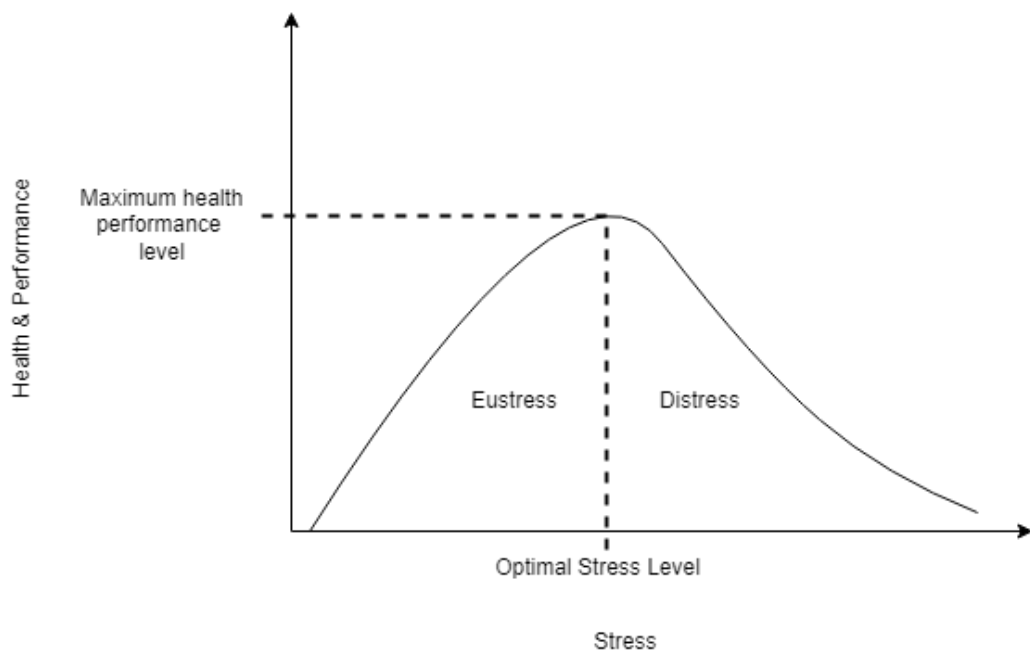


Figure 1.1 The level of stress that influences the health performance level (Selye, 1975)

As the stress level increases, the health or performance would improve. The feeling of 'pressure' can help push us going through a highly intensive situation. With a quick, our body can return to a resting state without causing any negative impact on health if stressors stay short-lived. However, a stress level incrementing, a point of maximal return reached. This point is known as optimal stress level. After achieved level, the following incremental in stress level is becoming harmful to the body.

When stress responses are active over time, it causes us to feel overwhelmed and unable to cope in interacting with the surrounding environment. Overwhelming stress feeling over a period called chronic; long-term stress affects both physical and mental health. Stress is a body's response to a threat in a situation, and anxiety is a reaction to the stress.

Stress usually causes negative emotions like anger, shame, and anxiety which refers to negative conditions, showing a relationship between stress and negative emotion. Lazarus and Folkman introduced a theory that stated stress and emotion depend on how an individual evaluates transactions with environments. If people find themselves unable to cope with transactions, they tend to be stressed.

The research concludes that stress and negative emotions are closely associated. The nervous systems serve as the foundation of the stress response. Environmental events (stressors) may either "cause" the activation of the stress response (as in the case of sympathomimetic stressors) or, as is usually the case, simply "set the stage" for the mobilization of the stress response. The cognitive-affective domain is the critical "causal" phase in most stress reactions.

Individual interpretation of the environmental event creates most stressors and subsequent stress responses. The locus coeruleus, limbic complexes, and the hypothalamic nuclei trigger efferent neurological, neuroendocrine, and endocrine reactions responds to higher cognitive-affective interactions.

Because the stress response axes are extraordinarily mobilized, target-organ activation is realized. The final step before pathogenic target-organ activation is coping. Here, the individual could act environmentally or cognitively, or both, to reduce or mitigate the overall amplitude and level of activation that reaches the target organs. However, when the stress arousal is excessive in either acute intensity or chronicity, target-organ dysfunction and/or pathology will result.

Emotional and physical stressors can be detrimental to the human body. The effects of stress on human wellbeing and symptoms have been extensively researched in recent times (Otto, 2014; Tripathi et al 2016). Kim (2021) found that people in their 30s experience the highest stress level due to mask-wearing.

In the early stage of stress detection, the researchers used a survey-style method that relies heavily on psychological questionnaires (Cohen et al 1983) and consultations (Dupere et al 2017). The researchers established the stress detection technique based on human physiological markers that act as golden measurements. However, this method requires a machine with cables attached to an individual. The method is not suitable for deployment anywhere outside the laboratory. A special space with the desired machine is required for mentioned motive.

In the modern research field, researchers have explored the non-invasions method for stress detection. Researchers contributed a variety of solutions to detect human stress remotely overcomes the limitation of stress detection based on the psychological signal. Skin temperature is one of the established stress markers based on physiological signals. The amount of heat dissipated by the body thru the skin has a capacity as a tool to measure the temperature of the human skin. Internal body activities such as blood flow, metabolic activities, subcutaneous tissue structure, sympathetic nervous (SNS) activities, and muscle contractions (Gillan, et al., 2013; Mizuno, et al., 2013; Taylor et al 2006) influences the body temperature.

The healthy people's body temperature is between 35.5°C and 37.7°C under normal conditions. The human body can regulate body temperature to keep it stable (Jones, A reappraisal of the use of infrared thermal image analysis in medicine, 1998). A noticeable rise in core body temperature may indicate an illness such as fever or hypothermia and a change in the human affective state (Jones & Plassmann, Digital infrared thermal imaging of human skin, 2002). Hypothalamus is a part of the brain located at the brain base responsible for regulating body temperature. Sometimes it may fail to function well under abnormal conditions (Khan & Mehmood, 2008; Fujimasa & Chinzei, 2000). However, neglecting treatment of the symptom of continuously high body temperature may lead to harmful consequences; injures body organs.

Another factor that affects human temperature is muscle contractions that generate heat through muscles movement (Bale, 1998). The internal body heat is transferring from the internal issue to the human skin via the blood supply in the vascular system. The control of blood flow in the skin by the processes of

vasoconstriction and vasodilation processes is part of the thermoregulatory mechanism, i.e., the thermal homeostasis of internal body temperature to external factors such as cold and heat (Khan & Mehmood, 2008; Fujimasa & Chinzei, 2000; Bale, 1998; Hessler & Abouelenien, 2018). The skin surface is an essential body part in regulating core body temperature: the body heat diffuses to the skin via internal vessels and the skin loses the heat in several ways: evaporation, thermal radiation, conduction, and exhalation through a respiratory process (Zhao et al 2018; Barclay & Launikonis, 2021; Youssef et al 2019; Khan et al 2009).

Pavlidis and team firstly discovered the alarming thermal signature and announced an increment of blood demand in the periorbital region (Pavlidis et al, 2002; Pavlidis I, 2003; Pavlidis et al., 2001; Pavlidis, et al., 2007; Pavlidis, et al., 2012). Consequently, it contributes to effective feature extraction, thus providing extensive research on the physiological signals of the human body such as breathing (Pavlidis, et al 2001), sweating (Pavlidis, et al., 2012), blood flow velocity (Ebisch, et al., 2012; Ioannou, et al., 2013), and heart rate (Pavlidis, et al., 2007).

Researchers explored the possibility of stress detection with facial skin temperature (Hong, 2020; Adachi et al 2019; Oiwa & Nozawa, 2019). Researchers also investigated other modalities such as pupil dilation, breathing pattern, behaviour pattern, keystroke pattern, and social media activity. In (Khan, et al 2009; Gao et al 2014; Zhang et al 2019), the researchers proposed a novel method to detect stress based on facial expressions. The results demonstrated that the proposed method has similar accuracy performance to other state-of-the-art methods. However, the proposed method requires RGB images. The same method can be replicated for thermal images

as a new potential research direction. Compared to other modalities, thermal-based stress detection provides a reliable accuracy rate concerning user privacy.

To investigate the facial skin temperature for human stress recognition, Mustafa et al. (2021) explored the recent use of thermal imaging in distinguishing human affective states and the problems that have surfaced. Mustafa suggested a framework for solving the issues discussed and the mentioned challenges.

Stress detection based on thermal imaging is popular because of its high characteristics ability to detect stress in thermal imaging without being influenced by the environment illumination. The human facial region is a common area for tracking because other human parts are always covered by the clothes and have privacy. The skin temperature dissipates when a subject is induced with stress. Stress detection is determined by quantizing the changes in skin temperature in the human facial region. Based on these characteristics, many researchers contribute a variety of algorithms to detect stress.

Throughout this study, we aimed to investigate the possibility to quantify the stress level based on the facial thermal signature. In addition, we investigate the effectiveness of lateral face side to provide insight information of skin temperatures distribution pattern when a person experiences a stress.

This chapter presented the purpose of this study, and the structure organized such as starts with the background of the study, followed by problem statement, research question, research objective, and significance of the study. The chapter also outlined the organization of this thesis.

1.2 Research Problem Statement

Two drawbacks have been identified for stress detection based on the facial thermal signature. The benchmarking of feature reduction algorithm is largely unexplored and the potential are unclear in improving the stress classification based on thermal features. Previous studies had utilized the feature selections algorithm to reduce feature dimensions to improve the accuracy of the classifications and avoid overfitting of the model. Even though few studies have proven that feature selection helped the stress classification, to the best knowledge of literature till the day. Feature selection algorithm is applied on the extracted feature from the thermal image, and mixed images together with visual images. Most of studies uses single feature selection algorithm to aid the classification. Understanding about benchmarking the different type of feature selection algorithm performance on the classifier and size of dataset is required. The combination of the feature selection and classification used might produce less accurate or unideal performance compared to the optimal combination of feature selection and classifier with considering the size of the data set. Moreover, the correct parameters influences the classification result. The classification result can be biased when no compatible parameter used. Hence, there is necessary to explore and analyse the existing feature selection algorithm and their impact in improving the classifications based on thermal features only.

Secondly, few studies are presented methodology to map the stress level with the facial temperature by using thermal image. The researchers contributed various hand-tailored algorithms to differentiate physical and mental states, detect acute stress and detect stress during cognitive load. However, the type of stress level such as

positive and negative stress topic is potential topic to be explored in thermal imaging. Hence this study remarks that it is necessary to conduct a preliminary study to estimate the stress level based on the facial temperature thermal feature extracted from vision-based thermal imaging. Also, more studies related stress detection based on facial expression in thermal imaging is required to establish deep understanding about stress detection in thermal imaging.

1.3 Research Questions

Therefore, two research questions developed for the current study:

1. Which the combination of feature selection algorithm with classifiers works best to classify the facial thermal features?
2. How the stress level can be estimated by using the thermal feature classification and facial thermal dataset?

1.4 Research Objective

This research aims to provide hybrid approach that combines feature selections algorithm that speeds up the feature classification that classify human stress based on thermal signatures. The research objective has been developed to achieve the goal:

1. To analyse nine thermal facial classification by combining feature reduction analysis and feature classifier.
2. To estimate human stress level by using the optimized thermal classifier that works best with feature selection algorithm together with based on various significant feature region of interests (ROI).

1.5 Research Scope and Limitation

The focus of this study is comparing the performance of the classifiers that combined together with the feature selection algorithm. Therefore, this study aimed to identify the best combination of thermal feature selection and feature classification to measure human stress. The input data of three expressions of the same person are used. Total 34 people images are used. The total number of images used are 112 images.

There are several limitations to this study. The data collection of the research is limited to dataset usage. Due to the Covid pandemic crisis, the experiment to acquire own data is prohibited as the students are not allowed into university. As that features and data originated from the dataset, this study is not capable to control the parameter of the data collection.

The limitation of this study is the usage of facial landmarks on thermal images. The evaluation of the effectiveness of the facial landmark is done manually. The area of research focuses on stress estimation and classification algorithms. In addition, the images that used in current works are expected to have facial landmarks correctly fitted on the image so that ROI can be segmented correctly. The thermal features are extracted from the segmented ROI. To avoid any bias or inaccurate results, the images used in the current work are assumed to have correct facial landmarks. We achieved it by manually selecting the thermal image that facial region successfully tracked by the employed model. In future, this is expected to be replaced with automation.

This research focuses on the stress classification based on thermal signatures of the facial expressions. The thermal signatures are extracted from the image of the facial expression. The extracted thermal signature is used for stress classification. The facial expressions selected in this study are smile, neutral and shock. Other expressions in the dataset are not included.

Due to the nature of the study, many algorithms could be selected for comparison. To control the complexity of the study, only three classifier algorithms are selected.

1.6 Contributions to the Knowledge

The main contribution of this study is as follows:

Firstly, the study presented the analysis of the all facial thermal classifiers that combines the feature reduction analysis and feature classifier that can classify the stress level based on the thermal signatures. To the best of knowledge in the literature, this is the first study in this domain that explored the feature reduction analysis and investigated the best combinations. A total of nine classifiers have been evaluated to find the best model for each ROI. Overall, 60 thermal features classifications have been evaluated with different sets of features in the current work.

Secondly, this work presented hybrid approach can be applied using edge computing provided that the dataset is fully trained (see appendix A-E). Copyright was obtained for proposed methodology implementation in edge computing.

Third, this study provides the preliminary result of the facial landmark detection in the thermal image without being aided by visual RGB. This result provides evidence that stress detection methodology can be applied without an RGB camera by using the Media Pipe model. With the proposed stress detection based on the thermal signature of the facial expressions, these findings can progress into future work that expands the horizon of thermal-stress related research. The current study proposed a feature reduction analyse classifier algorithm that aims to classify the features based on small datasets. The algorithm was developed based on facial expression in thermal imaging. This finding can expand the horizon of thermal stress-related research. The current study also presented the findings of stress estimation between positive and

negative stress based on the surface temperature computed from the thermal image. The study also presented insight into the stress estimation based on gender.

Lastly, the study provides insight knowledge about classification and feature reduction algorithm performance related to dataset size. Current study findings shows that Decision Tree (DT) algorithm fused with feature reduction analysis can perform better than Support Vector Machine (SVM) and Logistic Regression (LR) algorithm when using the small thermal image dataset. Moreover, with a big dataset, SVM and LR can perform better, and the accuracy can be improved with feature reduction analysis. This is first study to provide insight related to thermal human stress detection field.

1.7 Thesis Overview

This thesis is structured as follows.

Chapter 2 discusses the recent and related literature on stress detection based on thermal imaging.

Chapter 3 describes the methodology to conduct this study. This chapter introduced the proposed method as the framework of the solution.

Chapter 4 presents the study findings and provides an in-depth analysis and discussed findings.

Finally, Chapter 5 summarize our work in this thesis, review about contribution of the study and outlines the future directions for current work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The aim of this literature review is to provide a general overview of the literature reviews on human stress detection based on facial thermal signatures. Due to the invasiveness characteristic of the thermal image to detect human stress, this method become a popular subject in the stress detection field. First section of this chapter gives a brief description of stress detection based on facial thermal imaging. Second sections presented the type of thermal data used in the literatures. The methods used to detect facial region in thermal image are presented in third section. Fourth section provides the stress stimulus used in studies to stimulate the stress among subjects during data collections. Then, techniques used for features extraction are presented. The following sections describes the correlation studies between facial thermal signature and stress state. Next, stress classification based on facial skin temperature that measured by thermal imaging technology is given. Finally, the deep learning technique used for stress classification based thermal signature are presented.

Table 2.1 summarized the modal that are used to research the human stress state recognition.

Table 2.1 Literature work of human stress state recognition

Author	Year	Modal	Feature	Result
(Hirt, Eckard, & Kunz)	2020	Eyes activity	Pupil Dilation	Correlation, $\rho = 3.66 \times 10^{-7}$, achieved between pupil diameter and stress perceived by participants.
(Yamanaka & Kawakami)	2009	Eyes activity	Pupil Diameter	Pupil diameter larger when participant experiences mental stress. Study established a strong correlation between pupil diameter and heart rate variability, with a correlation coefficient of .896 ($p < .01$)
(Gunawardhane, Silva, Kulathunga, & Arunatileka)	2013	Key stroke	Key stroke pattern and dilation	Due to the nature of fast typing people, the keystroke behavior assumed contribute to the negative numbers which introduces bias in calculating significant differences.
(Lin, et al.)	2014	Interaction on social media	User engagement on social media	The proposed modal produces accuracy of 76.78% in detecting user stress based on twitter post.
(Han, Byun, & Kang)	2018	Speech signal	Pitch Jitter Energy Speaking rate Length of pauses	Proposed algorithm achieved 66.4% accuracy in detecting the stress state.

(Giannakakis, et al.)	2017	Facial Expression	Active Appearance Model (AAM)	The studies shows that best classification accuracy of 91.68% using Adaboost classifier.
(Zhang, Mei, Liu, Yuan, & Qian)	2019	Facial Expression	Multi-task Cascaded Convolutional Networks (MTCNN)	Proposed method provides accuracy of 93.6% in classifying the stress state
(Gao, Yuce, & Thiran, 2014)	2014	Facial expression	3D scale-invariant feature transform (3DSIFT)	Proposed system yields 83.09% accuracy
(Zhai & Barreto, 2006)	2006	Skin temperature	Slope of Skin temperature	The studies outcome shows that correlation between emotional stress and the physiological signals. A 90.10% accuracy rate was produced.
			Mean of Skin temperature temperature deviation temperature standard deviation	
		Galvanic Skin Resistance (GSR)	Number of responses Mean value of GSR Amplitude of Response Rising time of Response Energy of Response	
(Shi, et al., 2010)	2010	Heart rate	Mean Deviation Deviation squared	Study presented the SVM—based models to identify stress based on physiological signals.

2.2 Stress Detection Based on Facial Thermal Imaging

Thermal imaging is one of the popular topics among researchers to detect stress in a non-invasive manner. Thermal camera technology was initially unfeasible due to its low resolution, high cost, and heavyweight, combined with the ability to regulate the surroundings for a steady ambient temperature (Cho & Bianchi-Berthouze, Physiological and affective computing through thermal imaging: A survey, 2019). Thermal system inventions further paved the way for new varieties of accessible and adaptable thermal sensors that are lightweight, low-cost, and have high resolutions, such as handheld thermal sensors. As a result, sophisticated thermal sensors encourage researchers to investigate thermal imaging in laboratories and real-world settings in many applications, including human stress recognition (Selye, 1976).

Moreover, the Covid-19 pandemic enhanced the ability of thermal sensors. It can detect human face temperatures in a non-invasive and contactless manner. Autonomous Nervous system (ANS) is responsible for coordinating human physiological signals such as heart rate, respiration rate, blood perfusion, and body temperature during human stress state from a psychophysiological standpoint. Thermal imaging can measure the temporal temperatures of the face (Abdelrahman, Velloso, Dingler, Schmidt, & Vetere, 2017). The usage of thermal imaging is a realistic solution to achieve stress detection in a contactless manner.

Several studies have also investigated thermal imaging to explore other psychological signals is correlated with human stress states like respiration rate, pulse rate and skin temperature. It has the potential to transcend the limitations of contact-based and intrusive physiological sensors (Cardone, et al., 2020). When thermal imaging to visual (RGB) imaging, studies have shown that thermal images have many

benefits over RGB images. The variation of human skin colour, facial structure, texture, ethical contexts, cultural distinctions, and eyes could affect the accuracy of the human emotion including stress state applied visual-based methods. Visual-based systems are also sensitive to illumination change. In unregulated settings, visual-based imagination techniques have unreliable recognition precision (Elanthendral, Rekha, & Rameshkumar, 2014). Thermal imaging, on the other hand, is light resistant and can be used in low-light situations.

The connection between the human stress state and the variety of skin temperatures is confirmed with the thermo-muscular and hemodynamic-metabolic components (Jones B. F., 1998; Barlay & Launikonis, 2021). Modern researchers have focused on thermal imaging that encourages them to gauge the transient temperature esteems from the selected facial region to detect the stress state. In the literature, a temperature difference observed between the left and right sides of the face, and temperature change in the periorbital and nasal facial regions that linked to human stress. However, the alteration in blood flow in the periorbital area allows measuring both instantaneous and prolonged stress conditions (Elanthendral, Rekha, & Rameshkumar, 2014). This method is a procedural step that begins with a thermal dataset or thermal signature data collection activity. Thermal imaging is typically used in laboratory experiments to collect data. Stress stimulation is applied to cause participants to be stressed, and their facial thermal signatures are measured. Subsequently, the pre-processing and feature extraction approach was adopted to extract facial features and classify them with a classification procedure. However, the accuracy of the performance for each method is varied. The approaches accuracy also depends on the number of chosen criteria, the feature descriptor, and the classification method in Table 2.2.

Table 2.2 Literature work of thermal-based human stress state recognition

Author	Objective	Result
(Zhu, Tsiamyrtzis, & Pavlidis, 2007)	Zhen Zhu contributed a novel method to segment forehead thermal signature to improve stress detection in thermal imaging.	76.3% accuracy rate is achieved in deceptive state classification
(Hong, et al., 2009)	Hong et al demonstrated that the variation of thermal patterns between emotional stress and physical stress.	This study revealed the potential of the periorbital and cheek as a stress marker. The prefrontal region have more hot pixels when a subject induced an emotional stress compared to the physical stress.
(Cross, Skipper, & Petkie, 2013)	Cross conducted a study to detect stress based on thermal signals.	Cross suggested that cheek region can be prominent feature for mental and physical stress detection. The results shows that thermal imagery analysis produces higher accuracy in estimating heart rate during physical task.
(A.Rajoub & Zwiggelaar, 2014)	Ahmad and his team attempted to study thermal variation in the periorbital region as a candidate for better deception detection.	The proposed method yields 87% success rate in detecting the lie/truth responses.
(Jenkins & Brown, 2014)	Jenkins and Brown studied the three-way correlation between forehead temperatures, frontal EEG and self-report.	The findings established that the right-domain group has a remarkable correlation while no correlation for the left-domain. This reveals the insight of the temperature variation dependent.
(Sorostinean, Ferland, & Tapus, 2015)	Sorostinean et al studied the temperature variation of a subject when engaging with a robot.	The study shows little correlation is proved with stress and claimed more studies are needed to support the findings.
(Haji Mohd, Kashima, Sato,	Haji proposed a new approach detecting stress in thermal images	The findings show that the forehead is highly correlated to stress.

& Watanabe, 2015)	based on SIFT feature to match RGB and thermal.	
(Abouelenien, Burzo, & Mihalcea, 2016)	Abouelenien et al demonstrated that thermal variations exist in participants.	His studies concluded that thermal imaging can be applied for non-invasions stress detections. The study have also proven that the fusion of thermal features with other physiological traits outperforms stress detection by single sensors.
(Baltaci & Gokcay, 2016)	Baltaci studied the stress classification-based fusion features of thermal and pupil.	The classification accuracy of thermal features only achieved 76% while the pupil-feature only produces 73%. The fusion of two features yields highest accuracy of 83.9%
(Hong & Liu, 2017)	Kan Hong proposed a method to assess stress in real-time.	The study has proven the correlation between stress markers with temperature variation in periorbital. It is proven that thermal imaging has the ability as a stress marker.
(Cho, Automated mental stress recognition through mobile thermal imaging, 2017)	Yho Choo proposed automatic stress recognition thru mobile thermal imaging	. In this study, Cho et al proposed Optimal Quantization and thermal gradient flow techniques to extract blood dispersions of the facial capillary. It contributed that have chances to discriminate multiple stress levels.
(Abdelrahman, Velloso, Dinger, Schmidt, & Vetere, 2017)	Abdelrahman et al suggested that the possibility to estimate and quantifying the mental load.	The study revealed that different levels of the Stroop test and the complexity of reading texts influences facial temperature variations that promising the measure of cognitive load.
(Powar, et al., 2017)	Nilesh explored thermal imaging to classify challenged individuals from deception.	The proposed method with features extracted from mid-wave infrared statistical features produces

		classification accuracy of 85%.
(Vasavi, Neeharica, Poojitha, & Harika, 2018)	Vasavi studied the ability of thermal signature to detect psychological of the subject. Vasavi proposed two methods of signal extraction on two regions.	Vasavi and colleagues proposed six methods to detect stress. Two of it uses to measure the stress responses based on thermal signatures. First method is Fast Fourier Transform (FFT) produces accuracy of 91%. And second method, fused of wavelet and FFT, yields 90.3%. The result proves better accuracy than a similar early experiment done by (Garbey, Sun, Merla, & Pavlidis, 2007)
(Vasavi, Neeharica, & Wadhwa, 2018)	Vasavi and colleagues applied regression modelling to identify the most prominent thermal feature for better stress detection.	This study achieves better accuracy than their previous study. This study also proved that periorbital is a good candidate as a thermal signature for stress detection.
(Kopaczka, Jantos, & Merhof, Towards Analysis of Mental Stress Using Thermal Infrared Tomography, 2018)	Kopaczka conducted an experiment to measure temperature changes over stress stimulation activity based on the GLCM feature.	This study established that the temperature variation occurs in the upper lip region when stress invokes.
(Stoynova, 2018)	Stoynova studied the thermography changes due to student cognitive load during knowledge assessment tests.	The results proved that thermal imaging can be an efficient tool to measure stress. A correlation between the face surface temperature and the results of the test was found, $R=0.82$
(He, Mahfouf, & Torres-Salomao, 2018)	Changjiang investigated the effectiveness of the face temperature as a marker for stress detection.	The mean of the nasal area temperature is sensitive to changes in the mental state. The correlation is achieved between mental stress and

		maximum facial temperature.
(Derakhshan, Mikaeili, Gedeon, & Nasrabadi, 2020)	Derakhshan attempted to identify good performing machine learning techniques to increase accuracy.	Result provides evidence that thermal imaging holds high accuracy in detecting deception compared to golden physiological measurement. This study also shows that perinasal and chin are the most engaging ROIs during mental state assessment.
(Panasiuk, Prusaczyk, Ggrudzien, & Kowalski, 2020)	Jared studied the impact of psychophysical stimuli impact on facial thermal emissions. They compared numerical analysis and deep learning methods to classify stress states.	The proposed modal yields mean classification performance of 88.21% with 5-fold cross-validation scheme.
(Hong, 2020)	Hong proposed a method to detect physical stress by maximizing thermal signature.	The proposed algorithms provides accuracy rate of 90% in classifying the baseline and physical stress.
(Reshma, 2021)	Reshma proposed a hybrid deep learning, a combination of Alexnet and Vgg-16, to detect stress	The proposed hybrid networks produces 96.2% accuracy, higher than the individual network and existing machine learning e.g. SVM and KNN.
(Kumar, et al., 2021)	Kumar proposed hybrid network, StressNet to classify the stress states in thermal video.	Stress-Net yields a mean square error of 5.845 s in estimating the signal. This proposed method produces an average precision of 0.842 for stress detection.

2.3 Thermal based Data Type

In previous literature, there are two types of data identified: static facial image and moving face. Initially, the studies begin with static facial image detection and recognize a few regions of interest on the facial. When Kan Hong (2020) conducting data collections, participants must restrict their head movement. In the real world, it is an impractical approach to instruct the subject to be static. This limitation emphasizes the importance to track the facial in motion. Several studies focused on automating facial detection in thermal imaging where the participant can move freely.

Most studies conducted self-experiment to collect their dataset. A laboratory experiment was conducted in (Hong & Liu, 2017;Stoynova, 2018;He, Mahfouf, & Torres-Salomao, 2018;Kandus, 2018;Engert, et al., 2014) to collect thermal images and other physiological signals. For moving image types, the researchers generated temporal-spatial-based as features for stress detection. Regardless of static and moving, the thermal image exists in two forms that are in colour-type and grey-type as shown in Figure 2.1 (a) Thermal RGB (blood vessel) image, (b) Thermal (gray) image, (c) Thermal RGB (whole face). For image (a) the signal extraction is performed thru blood vessel segmentation. In the image (b), the temperature is measured throughout the grey level and in (c), the colour represents the hotness region in the face. Face detection and feature extraction algorithm are different accordingly to image type, which is discussed in later.