

THERMAL IMAGING-BASED CLASSIFIER FOR  
AFFECTIVE STATES OF AUTISM SPECTRUM  
DISORDER (ASD) CHILDREN

BY

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## ABSTRACT

Children with autism spectrum disorder (ASD) are identified as a group of people with social and emotional difficulties. Most of them face challenges in giving the appropriate social response through facial expression and speech. Since emotion is the key to effective social interaction, it needs to understand the correct expressions of emotion and confessions. Emotion is a type of emotional state and can be detected through behavioural interaction, physical interaction, and physiological signals. In general, recognizing emotional states from physical interaction such as facial expression and speech to children with autism is often unexpected. Consequently, an alternative method has been suggested to identify emotional states through physiological signals. Although considered unobtrusive, most current methods require sensor to be patched on to the skin body to measure the signals. This is likely to cause discomfort for children and hide their true emotions. The study suggests the use of thermal imaging technique as a passive method for analyzing physiological signals associated with affective states unobtrusively. The study hypothesizes that the effect of skin temperature changes as a result of pulsating blood flow in the blood vessels in the anterior facial region can be correlated to different affective states for ASD children. As such, a structured experiment was designed to measure the thermal data resulting from the expression of the different emotional state induced using a set of stimuli. To determine vascular regions, the thermal distribution of the face image was analyzed using a grey level occurrence matrix (GLCM). Then, a wavelet-based technique was deployed for patterns detection in time series to spot changes in emotional states throughout stimuli. A set of thermal cues were extracted and statistically analyzed before being fed into the k-Nearest Neighbor (k-NN) classifier to identify the emotional state. In the study, the affective state classification model for typically developing (TD) children aged between 5 to 9 years old was used as a baseline to form an ASD classifier. The results from the classifier showed the efficacy of the technique and accorded good performance of classification accuracy at 88% in identifying the affective states of autistic children. The inter-rater analysis has been done to find the agreement between the classifier's output and the manual techniques used to detect the affective states in ASD children. The results posed a challenge for therapists to determine the states of ASD children manually through visual observation due to poor expression of contextual emotional states as compared to TD children.

## ملخص البحث

يعرف الأطفال المصابون باضطراب طيف التوحد (ASD) بأنهم مجموعة من الأشخاص الذين يعانون من صعوبات اجتماعية وعاطفية. حيث يواجه معظمهم تحديات في إعطاء الاستجابة الاجتماعية المناسبة عن طريق الكلام وتعبيرات الوجه. ونظرًا لأن العاطفة هي مفتاح التفاعل الاجتماعي الفعال، فإن التواصل يحتاج إلى فهم التعبيرات والإدراكات الصحيحة. فالعاطفة هي نوع من الحالات الوجدانية التي يمكن اكتشافها من خلال التفاعل السلوكي والتفاعل الجسدي والإشارات الفسيولوجية. وبشكل عام، لا يمكن غالبًا الاعتماد في التعرف على الحالات العاطفية للأطفال المصابين بالتوحد على التفاعل الجسدي، مثل: الكلام وتعبيرات الوجه. وبالتالي، تم اقتراح طريقة بديلة للتعرف على الحالات العاطفية من خلال الإشارات الفسيولوجية. لكن معظم الطرق الحالية تتطلب توصيل المستشعر بجلد الجسم لقياس الإشارات، وعلى الرغم من اعتبارها عملية غير جراحية إلا أنها تتسبب بإزعاج الأطفال وإخفائهم مشاعرهم الحقيقية. لهذا اقترحت هذه الدراسة استخدام طريقة التصوير الحراري كوسيط سلبي لتحليل الإشارات الفسيولوجية المرتبطة بالحالات الوجدانية بشكل غير ملحوظ. حيث افترضت الدراسة أن للتغيرات تأثير على درجة حرارة الجلد بسبب تدفق الدم النابض في الأوعية الدموية في منطقة الوجه الأمامية المقاسة مما يساعد على أن يكون لها تأثير مباشر على اكتشاف الحالات العاطفية المختلفة. لذا تم تصميم تجربة منظمة لقياس البيانات الحرارية الناتجة عن التعبير عن الحالات العاطفية المختلفة الناتجة عن استخدام مجموعة من المحفزات. ولتحديد مناطق الأوعية الدموية، تم تحليل التوزيع الحراري لصورة الوجه باستخدام مصفوفة التواجد ذات المستوى الرمادي (GLCM). ثم استخدام تقنية تعتمد على الموجات لاكتشاف الأنماط في السلاسل الزمنية من أجل التعرف على التغيرات في الحالات العاطفية عبر المنبهات. وقد تم استخراج مجموعة من الإشارات الحرارية وتحليلها إحصائيًا قبل إدخالها في مصنف النقطة الأقرب كي المعروف بـ (k-NN) لتحديد الحالة العاطفية. واستخدمت الدراسة نموذج تصنيف الحالة العاطفية من الأطفال الطبيعيين (TD) الذين تتراوح أعمارهم بين 5 إلى 9 سنوات كخط أساس لتشكيل مصنف اضطراب طيف التوحد ASD. أظهرت نتائج المصنف كفاءة التقنية وأعطت أداءً جيدًا لدقة التصنيف بنسبة 88% في تحديد الحالات الوجدانية للأطفال المصابين بالتوحد. وعبر التحليل الداخلي، تم التحقق من مصنف ASD مقابل طرق القياس التقليدية، حيث يواجه المعالجون تحديات للتشخيص من خلال الملاحظة البصرية لأطفال ASD بسبب ضعف التعبير عن الحالات العاطفية السياقية مقارنةً بالأطفال الآخرين.

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## **DECLARATION**

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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## DEDICATION

*This thesis is dedicated to my husband, Taufik Yunahar, who encouraged me to pursue my studies and put trust on my capabilities to handle the challenges of graduate life. I am truly appreciate and thankful for having you and our smart and beautiful children (Azman Arsyad, Ali Imran, Muhammad Faisal, late (Muhammad Hasan) and Husna). This thesis is also dedicated to my parents, Rusli Mahmood, Maznah Ahmad, Yunahar Saya and Zulfa Fakhruddin who have gave me limitless support and optimism to achieve my dreams. Thank you endlessly.*

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## LIST OF SYMBOLS

$\sigma$	standard deviation
$\mu$	mean
$\eta$	viscosity
$\lambda$	length
$P$	pressure
$Q$	heat
$\rho_c$	constant of heat capacity



## LIST OF ABBREVIATIONS

<i>ABA</i>	Applied Behavioural Analysis
<i>APA</i>	American Psychiatric Association
<i>ADDM</i>	Autism and Developmental Disabilities Monitoring
<i>ASD</i>	Autism Spectrum Disorder
<i>ANS</i>	Autonomous Nervous System
<i>AVA</i>	Arteriovenous Anastomoses
<i>AWT</i>	Analytic Wavelet Transform
<i>BV</i>	Blood Vessel
<i>BVP</i>	Blood Volume Pulse
<i>CDC</i>	Centre for Disease Control and Prevention
<i>CLAHE</i>	Contrast Limited Adaptive Histogram Equalization
<i>CV</i>	Cross-Validation
<i>CWC</i>	Continuous Wavelet Coefficients
<i>CWT</i>	Continuous Wavelet Transform
<i>DEQ</i>	Discrete Emotions Questionnaires
<i>DSM</i>	Diagnostic and Statistical Manual
<i>DWT</i>	Discrete Wavelet Transforms
<i>EDA</i>	Electro-Dermal Activities
<i>ECG</i>	Electrocardiogram
<i>EEG</i>	Electroencephalogram
<i>EMG</i>	Electromyography
<i>FFR</i>	Frontal Facial Region
<i>fITI</i>	functional Infrared Thermal Imaging
<i>FT</i>	Fourier Transforms
<i>FTTP</i>	Facial Thermal Feature Point
<i>GLCM</i>	Gray Level Co-occurrence Matrix

<i>GSR</i>	Galvanic Skin Response
<i>IAPS</i>	International Affective Picture System
<i>KTFE</i>	Kotani Thermal Facial Expressions
<i>LDA</i>	Linear Discriminant Analysis
<i>LWIR</i>	Long-Wave Infrared
<i>MWIR</i>	Mid-Wave Infrared
<i>NN</i>	Nearest Neighbour
<i>PCA</i>	Principal Component Analysis
<i>PDD – NOS</i>	Pervasive Developmental Disorder Not Otherwise Specified
<i>PNS</i>	Parasympathetic Nervous System
<i>PTSD</i>	Post Traumatic Stress Disorder
<i>RH</i>	Research Hypothesis
<i>RO</i>	Research Objective
<i>ROI</i>	Region of Interest
<i>SNS</i>	Sympathetic Nervous System
<i>ST</i>	Skin Temperature
<i>STFT</i>	Short-time Fourier Transforms
<i>SVM</i>	Support Vector Machine
<i>SWIR</i>	Short-Wave Infrared
<i>TD</i>	Typically Developing
<i>TDHF</i>	Temperature Difference Histogram Features
<i>VPA</i>	Vaginal Pulse Amplitude
<i>WPT</i>	Wavelet Packet Transforms
<i>2D – DCT</i>	2-Dimensional Discrete Cosine Transformation

# CHAPTER ONE

## INTRODUCTION

### 1.1 INTRODUCTION

Thermal imaging is defined as a process of improving the visibility of objects in a dark condition by detecting the infrared radiation emitted by the object's body and creating an image based on the information. Recently, thermal imaging has found numerous applications mainly in three different categories of subjects namely animals and agricultures, inanimate objects and humans and each of them has been extensively reported and discussed by (Rai et al., 2017). Thermal imaging has also been widely used in military and surveillance applications Hermosilla et al. (2017) where the heat signatures released by the human body are used to track individuals in a dark environment. In many of these applications, thermal imaging camera offers as the best device to measure temperature from a greater distance, non-invasively and can work in the light-off environment. In the study of Autonomic Nervous System (ANS), thermal imaging could provide a solution to non-invasive autonomic monitoring and ecological recording of ANS activity (Cardone & Merla, 2017). The correlation between the physiological signal measured in ANS activity indicated the possibility to compute the psychological states or affective states of an individual (Armon et al., 2014).

In a psychological perspective, an 'affect' in affective states is characterized as an approach to depict the experience of inclination or feeling and it is a reaction of an individual's interaction with stimuli. The affective states are developed from a combination of valence and arousal states where valence is the positive-to-negative of

the intuitively experienced state. Meanwhile, arousal is the product of activation of the ANS and can be measured subjectively. The affective state is also known as an emotion because it has been a subclass in the Circumplex Model. The Circumplex model is representing the Cartesian chart to indicate the human's feeling at a specific time. It is recommended that an affective state is marked depending on the two elements; valence (unpleasant to pleasant) and arousal (low activation to high activation).

The affective states can be measured through behavioural reaction, physical reaction, as well as physiological signals. The behavioural and physical reaction can be seen or observed externally and sometimes it can be pretended as it to be. Measurement via physiological signals is seemed to be more natural and 'honest' as it happens automatically and unregulated in our body system. However, in all the measurements of the physiological signals, the in-contact type of sensors is necessary to be patched onto the skin. As a result, the person who wears the sensor would possibly aware of its presence and this might influence his 'true' affective states.

The human face is the most directly and naturally exposed to communication and interaction, thus offering an excellent region for computational psychophysiology based thermal IR imaging. A few autonomic parameters, for example, breathing rate (Pereira et al. (2017); Alkali et al. (2017)), pulse (Hong & Hong (2016); Nkurikiyeyezu et al. (2018); Mestha & Xu (2015)), sudomotor reaction (Lee & Kim (2018)) and cutaneous blood perfusion (Cracowski & Roustit (2016); Paul et al. (2015)) have been evaluated through the examination of the regulation of facial cutaneous temperature. The feasibility of using thermal imaging to measure the affective states in an unobtrusive manner motivates the research study to further comprehend to the ASD children.

According to Nardelli Nardelli et al. (2015), the change in affective states can also cause variation in the skin temperature and this was also supported by the study conducted by (Cardone & Merla, 2017). The paper claimed that pulsating blood flow produces the strongest variation on the temperature signal. Since the ANS is at the forefront of biological temperature displays, controlling human physiological activities such as changes in muscle tension, respiration, heart rate Armon et al. (2014) and cutaneous blood perfusion, could provide grounds for observation of affective states reading. The two biological mechanisms that enable thermal observation of affective nature are subcutaneous vasoconstriction and emotional sweating. When activated by epinephrine released in the bloodstream, subcutaneous vasoconstriction is a threat response that minimizes the blood volume within vessels under the skin (Dcosta et al., 2015). The adjustments in the rate of blood flow changing the emitted thermal print. These thermal readings result in the identification of affective states as reported in previous research by (Cardone & Merla, 2017). Affective states may also change the temperature on the skin during the shift of moods within the six basic affective states Ekman (1992) that are happy, surprise, fear, anger, disgust and sadness.

It is common for the change of affective states in an individual to be recognized either as positive or negative emotions through the level of engagements or from a group of emotions displayed. Engagement is epitomized as behavioural feedback meanwhile emotions normally refer to the speech or facial expression. In the case of children with Autism Spectrum Disorder (ASD) however, speech and facial expression are not reliable to gauge the emotions. Hence, the research study investigated on the other perspective of looking at the cutaneous blood perfusion under the skin on the facial surface for any cues of different affective states on these special groups of children.

Autism is defined by the presence of complications in the area of social deficits and communication problems. Meanwhile, Autism Spectrum Disorder (ASD) is recognized as "spectrum disorder" because it affects individuals differently and to varying degrees. In 2013, the most recent version of the Diagnostic and Statistical Manual (DSM) of Mental Disorders which typically referred by clinicians and therapists to analyze psychiatric diseases known as the DSM-5 was released. The DSM is published by the American Psychiatric Association (APA) and covers all classifications of psychological wellness issue for both adults and children. According to DSM-5 ASD, Harker & Stone (2014) encompasses of Autistic disorder, Asperger's disorder, and pervasive developmental disorder not otherwise specified (PDD-NOS). According to Centre for Disease Control and Prevention (CDC)'s Autism and Developmental Disabilities Monitoring (ADDM) Network, in 2014, it was estimated that about 1 in every 58 children was identified as having ASD across 11 ADDM sites in the US and 85% of them was referred as having Autistic disorder (Baio et al., 2018). Meanwhile in Malaysia, according to the National Autism Society of Malaysia (NASOM), 300,000 individuals were living with ASD from various ages (Radhi, 2018)(Koshy, 2018). Expressing affective states play a crucial role in having a noble social relationship, however, the deficiencies in the individuals with ASD might account for problems in social and communication development and stance challenges to their interest in communicating and socializing with others. Affective states recognition can be achieved through the study of affective computing. In the research study, it is paramount to identify features or thermal cues to consistently recognize the affective states of the children under the spectrum.

## 1.2 PROBLEM STATEMENT

The conventional method requires the therapists or caregivers to recognize the affective states of the autistic children through behavioural reaction subjected to their experience in interpreting the states using Applied Behavioral Analysis (ABA) tools. ABA tools include controlling elements in the environment and observing before-and-after behaviour (consequences) in interactions. The systems are enforcing positive rewards, as a way to teach an appropriate response in people with autistic disorder. The limitation posed by poor experience, however, may lead to wrong interpretation, thus causing unnecessary tense and stress to the children. Besides, a meta-analytic review of 39 studies Trevisan et al. (2018) had come out with equivocal findings that the person with the autistic disorder has impaired in expressing affective states through facial expression. Atypical use of facial expressions is the main factor that contributed to the deficits in social communication and social interaction. Their facial expressions are regarded as much more strange, uncommon, mechanical or otherwise inappropriate in appearance. Across studies, the facial expressions of people with autistic disorder are less likely to imitate others' expressions that may contribute to the expressions of others and also add to the affective states identification deficits prevalent to the ASD population. To circumvent this problem, many kinds of research have started to focus on the measured physiological signal to identify the affective state of autistic children. However, most of the methods require specialized sensors to be in-contact with the subject skin to measure the signals. As a result, even though they are non-invasive, the approach could distract and mask the 'true' emotion. Moreover, the approach may even exaggerate the issue of sensory difficulties of the autistic children which could lead to an inappropriate behavioural response.

### **1.3 RESEARCH PHILOSOPHY**

The deficiencies in physical and behavioural reactions to express emotion leads to the measurement of physiological signals to identify the autistic children's affective states. As the current method of detecting the affective state of the children under the spectrum poses a great challenge due to the invasive and intrusive method that requires an in-contact sensor on the skin. The study proposes to use thermal imaging as an unobtrusive technique to detect the true affective states of the autistic children. The ability of thermal imaging to measure the affective states even in a 'masked' emotion usually expressed in facial expression form for normal children motivates the study to be extended to investigate the affective states of autistic children. The accurate identification of affective state would be able to help enhance the performance of current rehabilitation and training regimens. Based on my best knowledge, this is the first attempt to study the affective state of children with the autistic disorder by using thermal imaging.

### **1.4 RESEARCH HYPOTHESIS**

As the affective states are closely related to the ANS of a person, it is most likely, those states can be identified if the physiological signals transpired from the ANS activation on certain parts of the body. As a result, 'true' affective state may not be able to be masked. The study hypothesizes that the proposed method of using thermal imaging would improve the performance of affective state identification process as it is more natural, and the subject could be made unaware of the presence of the measurement system. The research hypothesis could then be summarized as follows:

1. 'True' affective states cannot be masked if the subject is unaware of the presence of the measurement device.



2. The pattern of thermal imprints from the frontal face could indicate the certain class of affective states regardless of the presence of facial expression.
3. Human body contains thermoregulation mechanism to maintain the body's temperature at a nearly constant set-point. The change of affective states is correlated to the change in body temperature, thus considered as one of the disturbance variables that could change the set-point momentarily.

## **1.5 RESEARCH OBJECTIVES**

Based on the problem statements, the main goal in the study is to develop an affective state identification system for autistic children using cues from frontal face thermal imaging imprints. The main goal is streamed into three Research Objectives, which are:

1. To design an experiment to induce thermal imaging data for different affective states using a standardized set of stimuli.
2. To develop a specialized algorithm to process the thermal images for thermal cues extraction and selection for affective state classifier.
3. To verify the performance of the classifier of affective state model of ASD children against traditional method of affective state detection.

## **1.6 RESEARCH SCOPES**

The study was designed to classify three classes of affective states for Autism Spectrum Disorder (ASD) children using an unobtrusive device as a measurement tool. A classification model was initially developed based on a dataset from the typically developing (TD) children as a reference model. A set of questionnaires was used to first form the

superior classification model before further extend to the autistic children. The nature of the study practised was an individual session using a visual stimulant to induce the specific affective state and the frontal facial responses were recorded by a thermal camera. The three classes of affective states in Russell's Circumplex model investigated in the research were represented by Quadrant I, II and III as Happy, Fear and Sad respectively. The arousal-valence assessments were referred since it is easily interpreted (i.e feels good, feels bad) by children contrary to the discrete affective states. The research study implemented a cross-sectional approach in data collections where two groups of samples were recruited; TD children and ASD children. Random sampling was applied for the TD children whilst a purposive sampling was used for the children with autistic disorder in the advance group of behavioural analysis. The age of the samples from both groups was ranging from five to nine years old.

## **1.7 THESIS OUTLINES**

The thesis comprised of five chapters and appendices. It is presented as follows: Chapter 2 discussed and analyzed the literature reviews related to affective states measurement and detection using thermal images, delivered information on availability algorithms and finally discussed the classification method. Chapter 3 elaborated in-depth the proposed frameworks that were applied on thermal images in affective states detection for ASD children in which a complete explanation of the experimental procedures, the thermal images processes and development of classification model was presented. The experimental results were then tabulated in Chapter 4. Finally, the exclusive conclusion was written in Chapter 5 with some highlights on the limitation of this research study and the recommendation for future works.

# **CHAPTER TWO**

## **LITERATURE REVIEW**

### **2.1 INTRODUCTION**

In this chapter, a concise review associated with affective state theories and identification methods was presented. The previous and on-going researches in the area of affective state detection based on thermal imaging were emphasized accordingly. Numerous benefits and downsides of relevant topics from current literature were thoroughly discussed to highlight and identify the research gap, and to recommend feasible improvements from current models. The affective state detection is a complex interdisciplinary domain which is theoretically rooted in the study of psycho-physiology. Research done from the perspective of psychology and engineering fields reported that assessment methods of the affective states mostly relied on two methods which are, physiological signals measurement (EEG, heart rate, blood volume pulse (BVP), galvanic skin response (GSR), electro-dermal activities (EDA)) and self-report (questionnaire). These two methods attend to different research approach, however, share a similar objective that could be combined by computing the correlation between them. The physiological signal measurement used to study the involuntary process of sympathetic activities resulted in Autonomous Nervous System (ANS) activation whereas the self-report assesses the affective state experienced by the subject.

Review on topics related to research objectives stated earlier in Chapter 1 was covered in Section 2.2 until Section 2.3. Section 2.2 begins with the previous works on the topic of detection of affective states based on thermal imaging. Section 2.3 describes

the process of gathering data collections with the preparation of an effective method for inducing affective states. The possibilities in thermal images analysis were discussed and this was followed by the elaboration of different classification methods in machine learning.

## **2.2 DETECTION OF AFFECTIVE STATES FROM THERMAL IMAGES**

For decades, numbers of research have been conducted in the field of affective state detection using numerous modalities and exploiting varieties of cues from the signal generated from ANS activation. To shed some light on the issue, a comprehensive comparison of available modalities and exploitable cues was presented. In general, the modalities available for affective state detection can be divided into three categories; behavioural response, physical reaction and physiological signals. The behavioural response is usually measured through the engagement or body language towards the activities whilst physical reaction is presented through facial and speech expression respectively. To some extent, these two modalities are not appropriate to be implemented since the special need children like autistic children are having difficulties in physically or behaviorally expressing their 'true' affective states. Hence, the other perspective of looking at the automatic response inside the body for the cues of different affective states was investigated. The chosen modality for detection of affective states via physiological signals which are directly proportional to the response from the body as the reaction of ANS activities was discussed.

The ANS is responsible for the controls and regulations of bodily functions. It is mainly divided into two branches named as sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). These two divisions are a compliment to

each other where they are self-reliantly dominant in different situations. For example, the parasympathetic system is activated during dormant “rest and digest” whilst the sympathetic system is predominant during exercise “fight and flight”. A detailed review of the reaction from these two divisions in specific tissues in the body has been discussed conclusively by (Johnson, 2018). Many tissues are innervated by both systems and they are called as Nervous Tissue.

Theoretically, the ANS can be measured through standards of physiological signals such as Electroencephalograms (EEG), Electrocardiogram (ECG), Muscle Activity or Electromyogram (EMG), Galvanic Skin Response (GSR), Electrodermal Activity (EDA) and Skin Temperature (ST). Physiological signals have numerous substantial benefits and being the most reliable for accessing human affective states. They are labelled as “honest signals” as they cannot be easily elicited by any mindful or inhibitory control (Hazer-Rau et al., 2018). They originate from the peripheral nervous system and central nervous system and it is automatically regulated in the body. They are spontaneous and strongly correlated with human’s affective states. The correlation between ANS and affective states has been discussed decades ago by Levenson Shiota & Danvers (2017) where he was able to find the changes in pulse rate in accord to five different affective states; Fear, Anger, Disgust, Sad and Happy. It is supported by recent study Shu et al. (2018), a meta-analysis of the correlation between individual affective state and changes in physiological signals were successfully proven in engineering context where they used a sensor to measure the related signals in response to the induced affective states. Moreover, there have been a large number of published works in the domain of affective state detection from physiological signals and the summaries are tabulated in Table 2.1 below.

Table 2.1  
Published research works on the physiological signals analysis in affective states domain

References	Physiological Signals					
	ECG	EDA	EEG	EMG	ST	RES
Gokay et al. (2015)	✓	✓				
Jang et al. (2015)	✓	✓			✓	
Basu et al. (2015)					✓	
Al-Galal et al. (2016)	✓		✓			
Kumar et al. (2016)			✓			
Mirmohamadsadeghi et al. (2016)	✓					
X. Hu et al. (2017)			✓			
Tian et al. (2017)	✓	✓				
Abtahi et al. (2018)			✓	✓		
Brás et al. (2018)	✓					
Wei et al. (2018)	✓	✓	✓			✓
Ganapathy & Swaminathan (2019)		✓				
Hameed et al. (2019)						✓

The EDA is a measurement method which measures the effect of permeability of sweat gland, which in turn controlled by the SNS of skin conductance of electrical signals. On the other hand, EMG is a measurement technique used to detect and amplify tiny electrical impulses due to contraction of the muscle fibres. Since face is the most directly exposed in communication, detection of affective states is focused on the Facial EMG. It used to measure the muscle activities especially at corrugator and zygomatic major muscle towards certain affective state elicitation. Meanwhile, EEG is a recording method used to measure the brain activities by recording the fluctuation of voltages resulting from ionic current within the neurons. Recent research by Cardone & Merla (2017); Basu et al. (2015); Kanat et al. (2015) have suggested that Skin Temperature due to the blood perfusion recorded from the body through thermal imaging could also be used as one of the tools in affective states detection.

Two biological mechanisms enable thermal observation of affective nature; subcutaneous vasoconstriction and emotional sweating. These mechanisms are activated by epinephrine released in the bloodstream to change the volume of blood within vessels under the skin (Dcosta et al., 2015). The adjustment in blood flow can change the emitted thermal print which enables the classification of the subdivisions for the Autonomous Nervous System (ANS) to identify the affective states (Cardone & Merla, 2017). They have suggested the use of functional infrared thermal imaging (fITI) for psychophysiological studies for assessing emotional arousal and response.

Although there are many ways to analyzing the correlation between affective states and physiological signals in the human body, the research work focuses on the facial skin temperature. It is because the face is directly exposed to social communication and interaction. Even though, the facial expression is the most rampant means used to identify the affective states Benitez-Quiroz et al. (2016), yet, these means cannot usually recognize the 'true' affective states because it is easy to hide a real facial expression. Moreover, they are not significant for people who cannot reveal their feeling or express their feeling verbally or may give an inappropriate facial response like autistic people. Poljac et.al Poljac et al. (2017) provides evidence of the differences in interpretation of facial affective expressions also highly related to the extent of autism traits at the individual level. Another study by Sato Sato et al. (2013) found that emotion expressions are less noticeable for children with autistic disorder and this gap may be related to social deficits. It was supported by Gross Giombini (2015) that the children with autistic disorder have impairment in identifying and interpreting emotions from facial expressions. On the same note, thermal imaging may detect the changes in temperature for masked fearful faces as well as masked happy faces (Kanat et al., 2015).

Thermal imaging is a passive technique used to create a heat map of objects appearing in a sight without an external lighting source. The human body does also emit electromagnetic radiation and it is called as thermal radiation. The radiation emitted by the human body is mainly at a spectral range of 12 microns wavelength and it falls within a passive band of the light spectrum. Thermal imaging has been widely used in military and surveillance applications Hermosilla et al. (2017) where the heat signatures released by the human body is used to track individuals in the off-light environment. This is done by determining the amount of infrared (IR) radiation emitted by an object. IR spectrum constitutes of the active infrared band (Short-Wave Infrared (SWIR)/Near-IR: 0.9-1.7  $\mu$  m) and passive infrared band (Mid-Wave Infrared (MWIR): 3-5  $\mu$  m and Long-Wave Infrared (LWIR):8-14  $\mu$  m ). According to Plank's law, the wavelength of the peak of electromagnetic radiation from an object is inversely proportionate to its absolute temperature. Since most of the objects are near to room temperature, thus, it radiates mostly in the passive IR spectrum. Thermal imaging is an example of technology in MWIR and LWIR. It is superior to visible imaging technologies as a result of thermal radiation will penetrate mists, smokes, dust and even aerosols more effectively than light so objects may be detected over a good vary of commonly difficult region conditions. It is a passive technique capable of imaging under each day and night-time conditions similarly.

The disparity in facial images at the different spectral range can be seen in the images in Figure 2.1. In the visible and SWIR spectrum, a clear image of the face with physical features was shown due to their technique of common reflective phenomenology whilst in the passive Infrared spectrum; MWIR and LWIR, displays of the amount of infrared energy emitted, transmitted, and reflected by an object. The anatomical fea-



tures like vein patterns and blood perfusion may be also observable in the MWIR and LWIR spectrum.

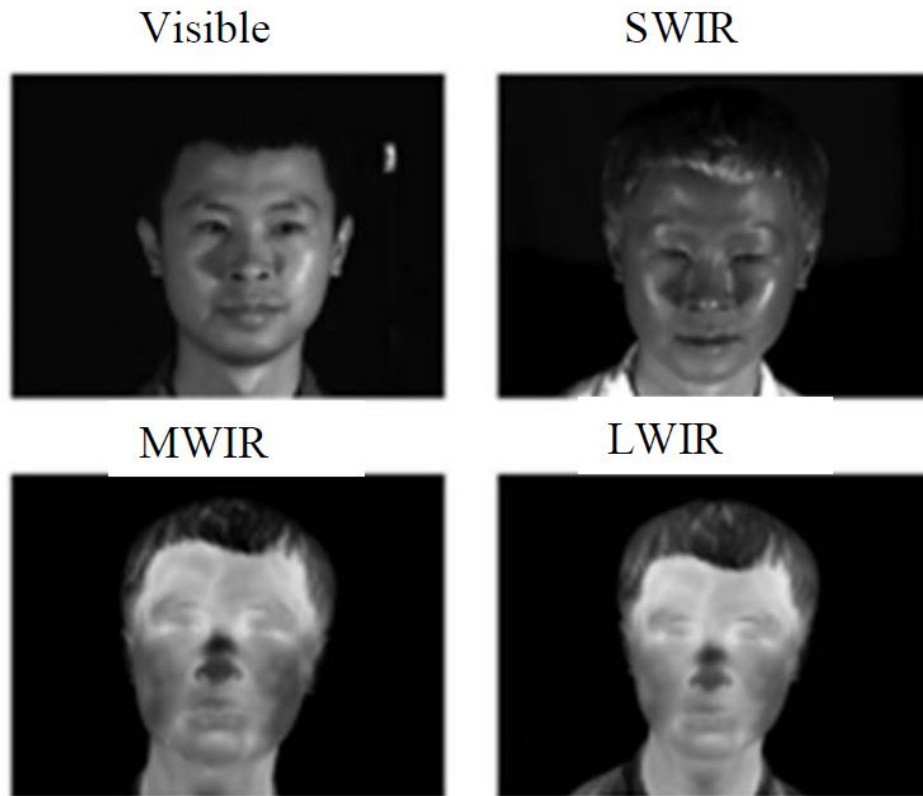


Figure 2.1: Face signature of a subject acquired in visible, SWIR, MWIR and LWIR S. Hu et al. (2015)

Thermal imaging has been successfully explored and employed in the medical area in which it introduces the use of unobtrusive and non-contact physiological sensors to the human body. It is a highly adaptable and delicate method to convert infrared light into temperature information, consenting wireless monitoring of the subject and detecting complex regional pain syndrome, inflammatory diseases, Raynaud's phenomenon Ring & Ammer (2012) and cancer Mambou et al. (2018). It works wirelessly with minimum contact to the human body and provide an upper hand in the solution as it can read thermal imprint from a distance of 4km Richards (2015) and can even work in the

passive-light environment.

Meanwhile, in a biological area, where affective states are construed from physiological signals, the thermal imaging gives an alternative method of non-invasive and seamless autonomous monitoring and assessing ANS activity. Kosonogov et al. has proven that thermal imaging provides a reliable tool that enables one to differentiate between affective states Kosonogov et al. (2017). Although these studies have evaluated the efficiency of thermal imaging in affective states detection, there was a missing gap in their research. They did not report whether this method is applicable for affective states detection in autistic children or not. It can be observed that the studies so far have focused on healthy people from various ranges of ages. Examinations on the specific group of autistic children have not been done.

According to Saxena et al. (2018), pulsating blood flow produces the strongest variation on the temperature signal. Nardelli Nardelli et al. (2015) found that the change in affective states causes variation in the skin temperature. This variation is notified for all of the tested affective states. Reported by Nisha Charkoudian (2003), variations in a skin blood flow response can be the result of changes in either the active vasodilator system or sympathetic vasoconstrictor system and it happens mechanistically as shown in Figure 2.2. Vasodilation process widens the vessels and thus increased the blood flow meanwhile vasoconstriction narrowed the vessels and lowered down the blood flow.

During the expression of specific emotions, a change in facial temperature would appear due to the thermoregulation mechanism in the body. Thermoregulation mechanism is a special, natural, body control system to maintain the temperature of a body at a relatively constant hypothalamic set-point. In this sense, the thermoregulation mech-

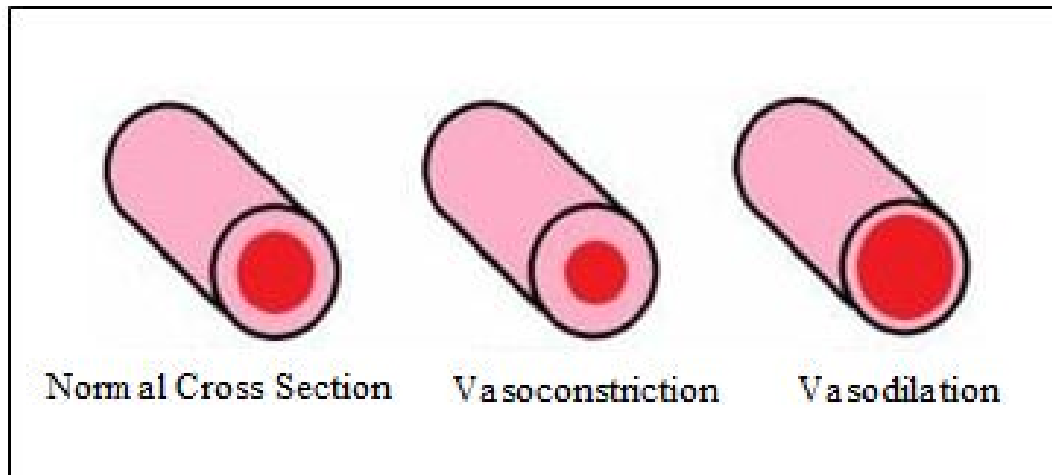


Figure 2.2: A cross-section of blood vessels taken from <https://biologydictionary.net/vasodilation>

anism could be designed as a model of control feedback loop system as depicted in Figure 2.3. The control feedback loops as in body thermoregulation mechanism. The change of affective states may cause a change in hypothalamic set-point or internal temperature. Then, it is sensed by the hypothalamus and resulted in the heat dissipation via cutaneous vasodilation to finally correct to the hypothalamic set-point.

The thermal readings are linearly correlated with the blood volume in the vessels. Merla et. al (2008), came out with a model to display the relationship between cutaneous blood flow and the temperatures of the cutaneous layers and the inner tissues. The method used has been validated by comparison with laser Doppler imaginary effect amongst twenty healthy subjects whereby, cutaneous blood flow values, simultaneously computed by thermal IR imagery and measured by laser Doppler imaging. The results depicted a linear correlation ( $R = 0.85$ , Pearson Product Moment Correlation). Therefore, it is possible to transform the raw thermal image series in the cutaneous blood flow image series. This method has been applied in psychophysiology study of emotion assessment Cardone & Merla (2017) and deception detection (Dcosta et al., 2015). As to

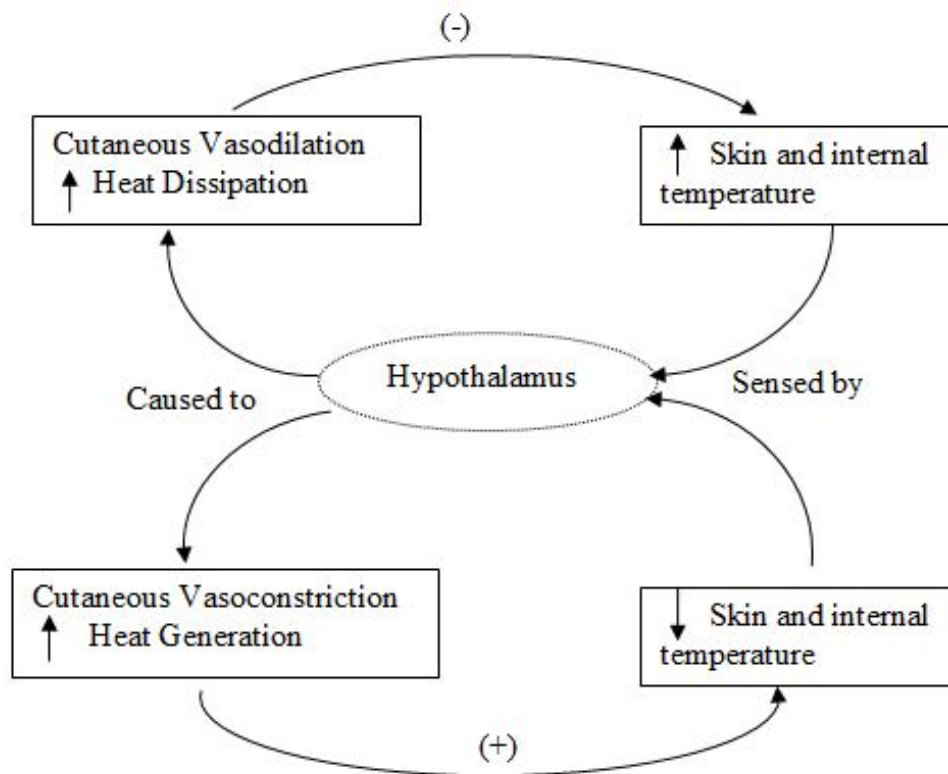


Figure 2.3: Mechanism in Body Thermoregulation

conclude, thermal imaging, bind the body’s naturally emitted thermal irradiation, allows temperature readings due to the variation in blood flow. This method enables cutaneous temperature recordings to be measured noninvasively, naturally, and contact-free.

Since the human face composition consists of thermal imprints that reflect the area with different concentration of blood vessel and hence it can be easily spotted using a thermal camera. These thermal patterns, particularly on facial skin, have been used for the analysis of the correlation between physiological signals and affective states. Correlation between the changes in facial skin temperature and affective states was significantly proven by Salazar-López et al. (2015) where the maps of bodily sensation temperature changes were studied in response to the visual stimuli.

The similar research Cardone et al. (2017) distinguished the changes in facial skin temperature due to redirected blood to the region of interest (ROI) on the face. The

disparity in facial skin temperature is caused by periorbital Levine et al. (2001) and supraorbital vessels Pavlidis et al. (2007) of the face wherein heat increases according to stressors that are believed to facilitate preparedness for rapid eye movement in fight or flight mode.

### **2.3 DEVELOPMENT OF A MODEL FOR CLASSIFICATION OF AFFECTIVE STATES FOR ASD CHILDREN**

Affective states or generally known as emotions play an essential role in learning, perception, rational decision-making, and a diversity of purposes as defined by (Ringeval et al., 2015). The inherent communication between people plays a significant character in human social interactions. However, in several cases, meaningful communication, especially for an individual with special needs like children with autistic disorder, becomes a nontrivial task.

Autistic disorder is a developmental disorder that negatively affects social interaction and communication. Typically favourable modalities of interaction such as body language and oral communication may be daunted which resulted in unachievable of meaningful communication. There is no medication for autism, and it is not curable. However, there are some treatments or therapies that can improve communications and social skills. Autistic children can behave and react closely to normal children after going through rehabilitation and intervention procedures. However, the therapies need to know and understand the children's affective states. In fact, in successful learning, the identification of the learners' affective state has demonstrated to be a vital feature (Elizabeth A. Linnenbrink, 2006). In educational contexts, it is important to emphasize that learning does not only include mental, social and psychomotor character, but also an affective component (Radin A Rahman et al., 2015).

Affection (an emotion) impact virtual learning, and during this course, the student can experience both positive and negative emotions, which can be seen as signs of success and frustration in learning (Kaushik, 2017). In this scenario, knowing students' affective states is fundamental to evaluate learning, to identify relationships between emotion and learning, and to establish strategies to adapt students' learning experiences, considering the dimensions effective (D'Errico et al., 2017). Therefore, a well-planned and systematic flow of the experiment should be considered to design for collections of thermal imaging data from typically developing (TD) children (control group) and children with ASD.

According to Ez-Zaouia et al. (2017), it is possible to infer subjects' affective state from information collected from different types of resources, such as audio, video, self-report tools and interaction analysis. Seeing the miscellaneous potentials of detection of affective states, in this research work, a systematic review of the literature was performed with the target of finding similar researches that address the detection of these affective states in thermal images and finally justify the techniques used. In the following sub-sections, the chosen algorithms for proper experimental procedures was discussed where it started with the stimuli used to induce the affective states, followed by the processed in the thermal images analyses and the classification method of affective states.

### **2.3.1 Stimuli**

The study of thermal imaging and affective state should carefully consider the stimuli to induce the affective states. Usually, affective state stimuli are taken to address arousal and valence states which are presented in many forms of modalities including

visual, hearing, physical and odour stimulation accordingly. This affective state inducing stimulus results in the elicit disparate biological system and physiological system for optimal affective responses. These responses can touch almost every facet of human being and include cognitive changes (e.g., changes in politeness), behavioural changes (e.g., body languages) and physiological changes (e.g. physiological signals). When a person has been induced with a specific emotion by visual stimuli, the limbic system in his brain region is activated and these result in changes in the skin surface temperature to regulate homeostasis.

According to Martins et al. (2016), audio-visual stimuli is widely used in emotional induction especially in the younger group and as a visual stimulus, it is understood to give more far-reaching processing in the visual cortex in the brain. The visual stimuli can be composed of film clips, words, or still images of faces, scenery, situation or objects used as affective state measurable. The visual aspect of the stimuli is based on several images that have been selected from the standard International Affective Picture System (IAPS) database. The images were then compiled into a video clip embedded with audio where this audio-video combination has been testified for emotion induction in (Bai et al., 2017; Mori et al., 2017).

### **2.3.2 Thermal Image Analysis**

The use of thermal imaging for affective states analysis has been reported with various methods and algorithms applied (Basu et al., 2015; Bijalwan et al., 2015; Panasiti et al., 2016; Cardone & Merla, 2017; Kosonogov et al., 2017; Kopaczka et al., 2017). Nevertheless, a standard golden procedure for thermal imaging processing has not been reported. Some researchers have implemented thermal images with a combination of

other physiological signals to detect affective states. Just as, Cardone & Merla (2017) has conducted feasibility research on fear conditioning experienced by Post Traumatic Stress Disorder (PTSD) patients specifically those with the mild condition. All the recruited subjects were victims of traumatic events in life for at least 10 months before the experiment was conducted. Throughout the study, the fear-conditioned responses were monitored by thermal imaging and endodermal activity (EDA) responses. The facial thermal response was recorded at the nose tip region; the temperature variation occurs due to distress and emotional response activated by the sympathetic nervous system as reported in several studies.

On the similarity work, facial thermal signatures were further analyzed in Kosonogov et al. (2017) for classifying affective states where three types of signals were combined; the thermal image, blood-volume-pulse and respiratory effort. Meanwhile, Cho (2017) has further examined the viability of thermal imaging for stress-related research. Several well-established physiological signals for stress markers such as heart rate, finger temperature, cortisol, and alpha-amylase were tested in their work against thermal imaging in terms of recognition power. Their findings found that thermal imaging approach did correlate with stress-induced mood, however, the accuracy, recognition power and ease of use were still lacking as compared to other well-established stress markers. They added that thermal imaging may be favourable to be used in a special population where complying with the standard instrument may cause problems in invasive monitoring and assessing psychological responses.

A segmentation of the frontal facial region (FFR) that is needed in the analysis was identified prior to performing thermal image analysis. A region of measurement should be selected in a physical region that is devoid of hair and has minimal fatty tis-



sue deposits. Levine et al. (2001) had experimented on facial skin temperature by using thermal imaging camera and he concluded that the change in temperature on the cheek is due to redirected blood to the eye musculature. Likewise, as reported by Cardone & Merla (2017) which also used the thermal imaging technique, noted that while the temperature of the nose decreased, behavioural signs of distress increased, whereas when those signs decreased, the nose returned to baseline values. This variation in temperature is notified for all of the chosen affective states. The changes are also reported on the other FFR such as on the upper lip. Most importantly, in areas devoid of hair and fatty tissue, such as the forehead, the primary contributions of heat originate from the minute temperature variations in the blood and core temperatures. This may be partly attributed to the comparatively large presence of a vascular network called the AVA (arteriovenous anastomoses) that enables wide-range control of blood flow to the skin. The AVA is controlled by the sympathetic nerves, and it is believed that temperature that changes sharply reflect the vascular constriction that occurs when nerve activity increases. The sympathetic nerve is a part of the autonomous nervous system where it is activated during fights and flight responses.

The figure shows specific heat patterns associated with the different muscle contractions. As a result, thermal imaging proves to be a useful tool to unobtrusively analyses fine-grained elements of facial expressions (Jarlier et al., 2011). Indeed, Kosonogov et al. (2017) and Cruz-Albarran et al. (2017) revealed the new marker of affective arousal via facial thermal imaging but yet the region of interest only focusing on the tip of the nose region. The nose is made the target due to the absence of primary muscles, which circumvents thermal impurity due to retrenchment and the existence of arteriovenous anastomoses that constricts and diverts the blood to the nose causing temperature

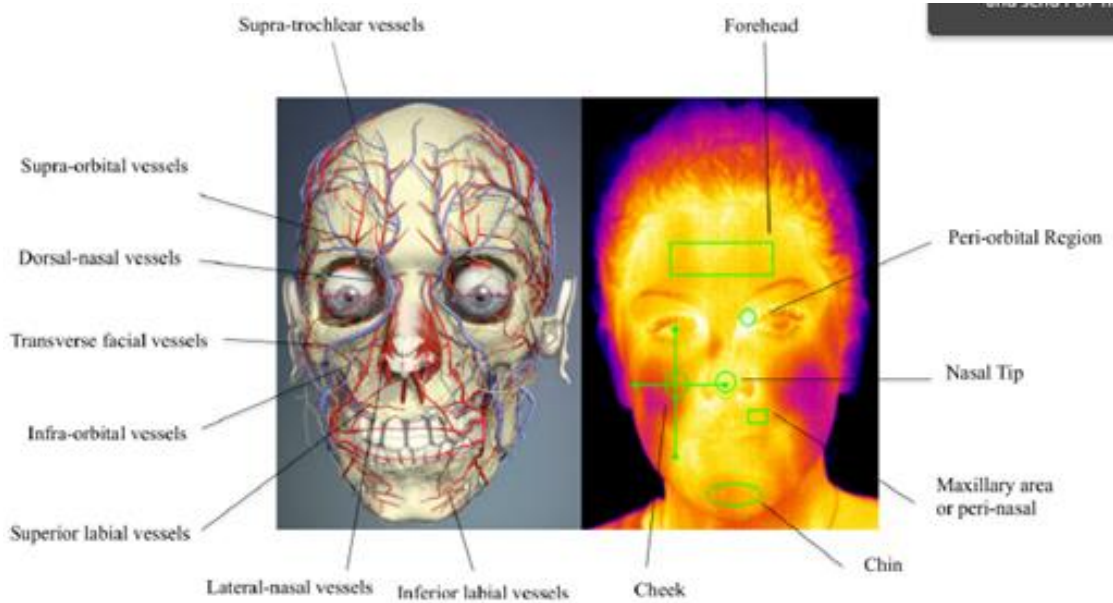


Figure 2.4: Thermal representation for extractions of ROIs on face

changes. On the other hand, the inter-relation between thermal body regulations on forehead experiment done by Cardone & Merla (2017) shows the existence of the temperature change in facial skin temperature in a stressful situation for the infant when introduced to strangers. These reviews show the maturity and continuous development of the thermal imaging analysis in affective state detection. Thermal imaging can be a useful non-invasive tool for affective states detection especially when standardize invasive tools become an issue to attach to the subject.

Features extraction from thermal images can be divided into two domains namely: imaging features and temperature features (Wang et al., 2012). Imaging features are defined as features processed directly on the image intensity values, meanwhile temperature features are the conversion values from intensity to temperature readings from each pixel in the thermal image. Among the researchers that use extracted imaging features from the thermal images is Yasunari Yoshitomi et al. (2010), where the extracted features are transformed by using a 2-dimensional discrete cosine transformation (2D-DCT) to transform the grayscale values in the facial area into frequency components,