e-ISSN: 2685-4090 http://ojs.uajy.ac.id/index.php/IJIEEM

Emotion Detection Research: A Systematic Review Focuses on Data Type, Classifier Algorithm, and Experimental Methods

Twin Yoshua R. Destyanto[1,2]

[1]Department of Industrial Engineering, Universitas Atma Jaya Yogyakarta, Sleman, Indonesia
[2]Department of Industrial Engineering and Management, Yuan Ze University, Taoyuan, Taiwan (ROC)

Email: twin.destyanto@uajy.ac.id

*Corresponding author

ABSTRACT

There is a lot of research being done on detecting human emotions. Emotion detection models are developed based on physiological data. With the development of low-cost wearable devices that measure human physiological data such as brain activity, heart rate, and skin conductivity, this research can be conducted in developing countries like Southeast Asia. However, as far as the author's research is concerned, a literature review has yet to be found on how this research on emotion detection was carried out in Southeast Asia. Therefore, this study aimed to conduct a systematic review of emotion detection research in Southeast Asia, focusing on the selection of physiological data, classification methods, and how the experiment was conducted according to the number of participants and duration. Using PRISMA guidelines, 22 SCOPUS-indexed journal articles and proceedings were reviewed. The review found that physiological data were dominated by brain activity data with the Muse Headband, followed by heart rate and skin conductivity collected with various wristbands, from around 5-31 participants, for 8 minutes to 7 weeks. Classification analysis applies machine learning, deep learning, and traditional statistics. The experiments were conducted primarily in sitting and standing positions, conditioned environments (for developing research), and unconditioned environments (applied research). This review concluded that future research opportunities exist regarding other data types, data labeling methods, and broader applications. These reviews will contribute to the enrichment of ideas and the development of emotion recognition research in Southeast Asian countries in the future.

DOI: https://doi.org/10.24002/ijieem.v5i1.7077

Keywords: emotion detection, emotion recognition, wearable device, smartphone, arousal-valence, classifier

Research Type: Review Paper

Article History: Received March 23, 2023; Revised May 17, 2023; Accepted June 12, 2023

How to cite: Destyanto, T.Y.R. (2023). Emotion Detection Research: A Systematic Review Focuses on Data Type, Classifier Algorithm, and Experimental Methods. *International Journal of Industrial Engineering and Engineering Management, 5*(1), 31-43.

1. INTRODUCTION

Detection of human emotional status, which is a development of human activity recognition (HAR), is currently an area that is widely practiced and provides broad contributions covering various applications (Al-Nafjan et al., 2017; Saganowski et al., 2020). In the realm of Ergonomics, the detection of emotional status is important to find out how the human body responds to its emotional state in response to working environmental conditions (Noelke et al., 2016; Mullins & White, 2019). Product design (Yadollahi et al., 2017), and even received service quality (Alsaggaf & Althonayan, 2018; Jain et al., 2018). Understanding changes in human emotional conditions like this can help to improve current environmental conditions or designs. Nonetheless, there are still wide opportunities to be mapped regarding this field, especially in developing countries, that will be beneficial for enlightening researchers to conduct further research.

Systems or models built to detect human emotional status can be carried out by utilizing various types of human physiological data (Al-Nafjan et al., 2017; Saganowski et al., 2020; Akçay & Oğuz, 2020) as well as subjective data (Akçay & Oğuz, 2020) collected through a variety of subjective emotional assessment tools. Physiological data that can be used include data on brain activity (Nakisa et al., 2018; Lu et al., 2019), skin conductivity (Pollreisz & TaheriNejad, 2017; Schmidt et al., 2018; Feng et al., 2018), eye movements (Alghowinem et al., 2013; Krithika & Priya, 2016), and also body heart rate (Dao et al., 2018; Fernández-Aguilar et al., 2019). The type of device can be in the form of fixed and complex medical measuring instruments such as medical electroencephalography (EEG) (Al-Nafjan et al., 2017) and electrocardiography (ECG) (Akçay & Oğuz, 2020). In addition, various wearable devices are currently used to collect physiological data such as smartwatches (Fernández-Aguilar et al., 2019; Kamdar & Wu, 2016; Yang et al., 2020). Portable EEG (Suhaimi et al., 2018b; Teo & Chia, 2018) and even smartphones (Yadollahi et al., 2017) to measure anthropometric motion through the accelerometer and gyroscope sensors embedded in them.

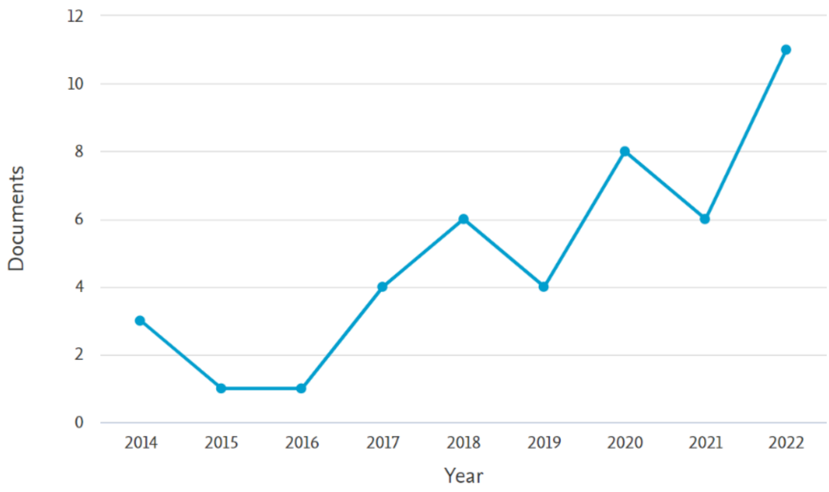
Participants can verify the data generated by the human organ activity recording device by filling out a questionnaire. Based on a certain level or classification of emotions, this questionnaire indicates the emotional status of the respondent. Emotional status classification can be in the form of categorical status (Nguyen et al., 2017; Wahyono et al., 2022), such as happy, sad, angry, etc., or in the form of an arousal-valence level scale (Dao et al., 2018; Suhaimi et al., 2018b) such as using Self-Assessment Manikin or SAM (Kanjo et al., 2019; Xu et al., 2019), and Positive and Negative Affect Schedule or PANAS (Schmidt et al., 2018). The contents of this questionnaire can be used as markers to label physiological data according to the emotional status felt by the participants. For a supervised emotion detection model, labeling efforts are essential so that the model can learn data patterns based on the labels.

The data obtained becomes material for building an emotion detection model that can describe a person's emotional state based on the pattern of collected physiological data. The data can be analyzed using various classification methods comprising Super Vector Machine (SVM) (Huynh et al., 2016; Nguyen et al., 2017), Decision Tree (DT) (Nguyen et al., 2017), Random Forest (RF) (Bin Suhaimi et al., 2020; Sofian Suhaimi et al., 2021), or applying deep learning methods such as Convolutional Neural Network (CNN) (Gonzalez et al., 2020) and Deep Neural Network (DNN) (Teo & Chia, 2018). This classification algorithm is evaluated based on parameters such as accuracy, recall, F-1 score, and precision.

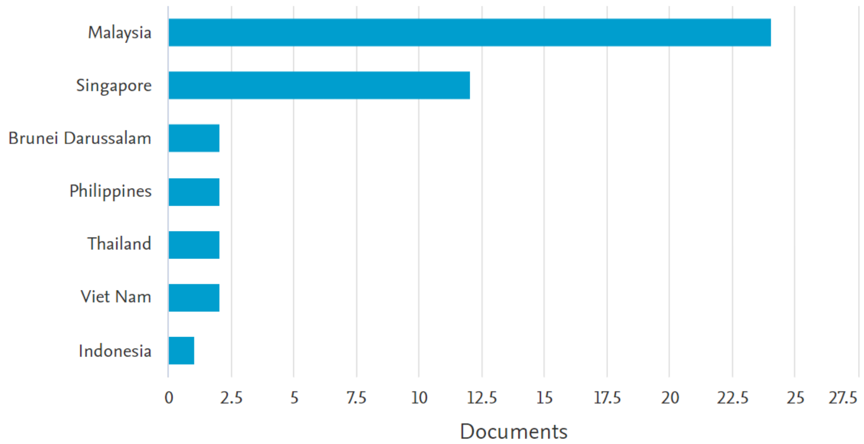
During this decade, research and development on this emotion detection model have continued to grow, particularly in Southeast Asian countries, which are mainly developing countries compared to East Asian countries. Emotion detection applications in Southeast Asian countries have become a recent need along with the development of how this region develops their goods production process (Naruetharadhol & Gebsombut, 2020; Prabowo & Aji, 2021), service design (Hartono, 2020), and well-being quality (Jaharuddin & Zainol, 2019; Kadariya et al., 2019), that involves users' emotion as one of consideration. Therefore, digging into the research development regarding emotion detection in this region become necessary to know the further research expansion opportunities.

An analysis of SCOPUS-indexed publications over the past decade illustrates the pattern of research that is continuing to develop in Southeast Asia. This trend can be seen in the comparison results in Figure 1. Figure 1 (a) shows the number of documents published per year, Figure 1 (b) shows the distribution of publications by countries in Southeast Asia, while Figure 1 (c) published research conducted in East Asian countries. The comparison shows that the number research on emotion detection recognition in Southeast Asian countries is much smaller compared to East Asian countries. However, the trend shown in (a) implies promising growth in this field in Southeast Asian countries. This development is supported by the ease of obtaining mobile devices at much more affordable prices (Valliappan et al., 2017; Godfrey et al., 2018) compared to complex medical devices, enabling researchers in Southeast Asian countries to conduct research to build real-time and non-invasive emotion detection tools. Diverse human factors in Southeast Asia, such as ethnicity, race, geography, and age groups, are potentially unique differentiators from similar research elsewhere. Despite the positive trend, the number of studies is still relatively small compared to the amount of research conducted around the world (Akçay & Oğuz, 2020).

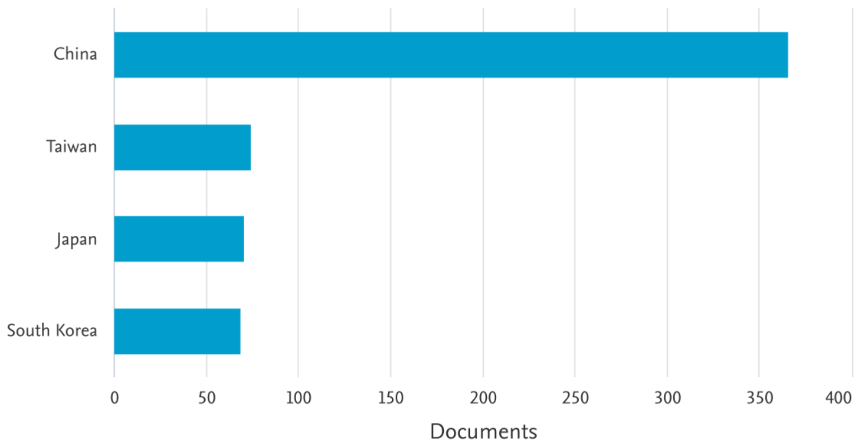
A systematic search for the development of research on emotion detection has been undertaken by several researchers, such as Al-Nafjan et al. (2017), who conducted a review of emotion detection using medical EEG. Dzedzickis et al. (2020) conducted a special literature review to obtain information about the types of sensors and methods of collecting physiological data utilizing both medical and mobile devices. In addition, a review was also carried out extensively by Akçay and Oğuz (2020), which summarized the use of voice data for detecting human emotional states. A search focused on emotion detection with wearable devices was carried out by Saganowski et al. (2020), who found that research in the area has advanced, but there is still room for development. These searches show that many emotion detection models have been studied in various countries. However, to the extent of the author's knowledge, there has not been a review of how this research on emotion detection was carried out in the South-East Asia region. The differences in demographics and resources unique to Southeast Asian countries compared to other regions make this regionally-focused review critical. They have the potential to contribute to providing an overview of experimental techniques, types of data and tools for collecting data, and methods of classifying emotional states. Therefore, this study aimed to systematically review how research on emotion detection through wearable devices is conducted in Southeast Asian countries. The research focused on finding out (1) the experimental techniques that were performed, including the size of the participants involved and the duration of data collection, (2) the physiological data type and



(a)



(b)



(c)

Figure 1. Analysis of SCOPUS-indexed papers on emotion detection using wearable devices in Southeast Asia over the past decade: (a) publication trends over the past decade; (b) the distribution of publications by the Southeast Asian country, (c) the distribution of publications by the East Asian country

wearable devices used to collect the data, and (3) the classification method used to detect emotional states. The search conducted is intended to gain a better understanding of Southeast Asia's current research map and research potential.

2. REVIEW METHODOLOGY

The study used qualitative research methods with a systematic literature review approach to accomplish its research objectives. The steps in this systematic review are divided into 3 phases (Haddaway et al., 2022). An

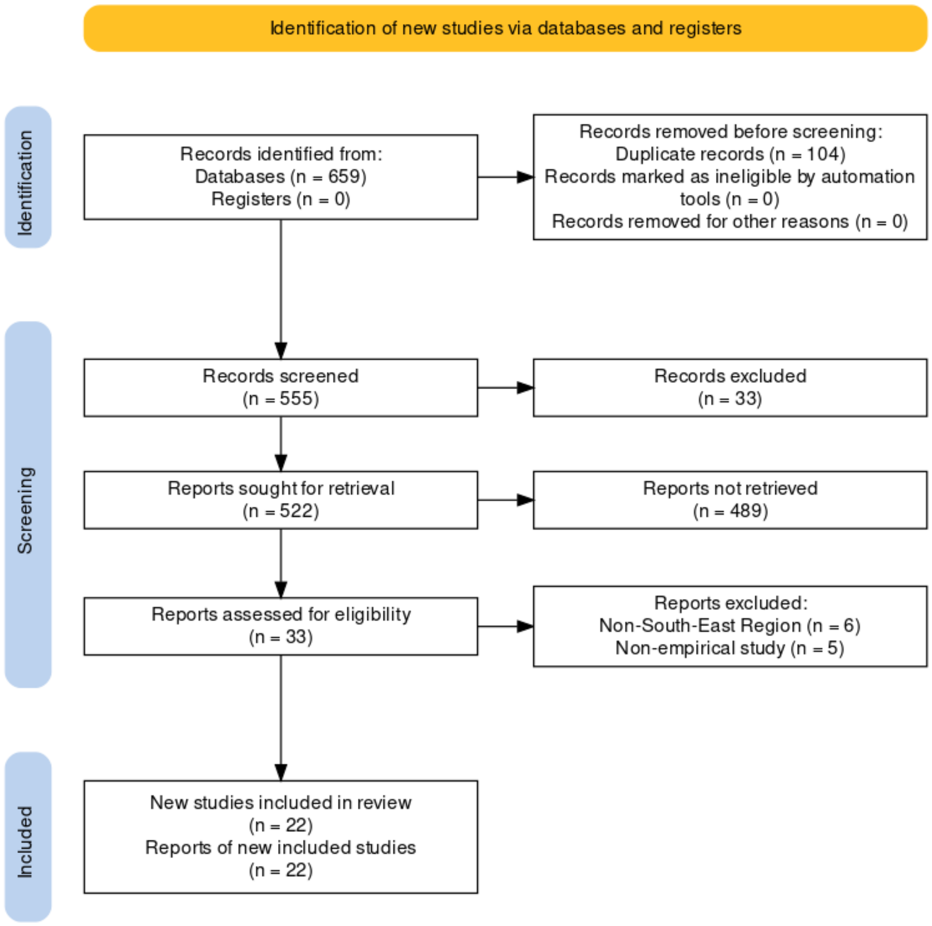


Figure 2. PRISMA flow diagram (Haddaway *et al.*, 2022) illustrates the literature search process in this systematic literature review

identification phase is the first step in the review, where a search is conducted based upon the purpose of the review, which is to determine what research has been conducted based on SCOPUS-indexed journal articles and conference proceedings relating to emotion detection with wearable devices over the past decade. The search was done from December 2022 to March 2023. The keywords for searching in the SCOPUS database were emotion detection, emotion recognition, wearable devices, and smartphones. 659 articles met these criteria. Furthermore, at this stage, the same articles were eliminated due to overlap when searching using different keywords, resulting in 104 articles being eliminated from the search results (the remaining 555 articles).

The next stage is the screening phase, which consists of elimination depending on the year of publication (2013-2022). 33 articles were eliminated, or the remaining 552 articles, after filtering. Afterward, we screened based on the country where the research was conducted, which led to eliminating 489 articles, leaving 33 articles. Further, detailed screening was conducted based on the title, abstract, and full text. It was found that six articles were not done in Southeast Asia, even though the author's affiliation was in a Southeast Asian country. Additionally, five articles that were not empirical studies but reviews were eliminated. In these articles, secondary data was gathered from other(b)studies rather than the author's own research. The screening at this stage resulted in the retention of 22 articles. The third stage is the last phase to ensure that the articles to be used are in accordance with the research objectives. The result of this review process is 22 SCOPUS-indexed journal articles and proceedings. The flow of this systematic literature review is summarized in the PRISMA flow diagram, as shown in Figure 2.

All the final articles included in this review were studied in detail. This was primarily to obtain information about the number of participants involved in the experiment, the duration of data collection, and the devices used to collect data. Information about the classification method and detection accuracy level was also inventoried regarding emotion detection. A K-Chart was then used to map the review results to illustrate research opportunities in emotion detection in Southeast Asia (Abdullah et al., 2006; Zaheer et al., 2020).

3. REVIEW RESULTS AND DISCUSSION

3.1. Selection of physiological data types and data collection methods

Most researchers in Southeast Asia use EEG data to detect emotions (Huynh et al., 2016; Suhaimi et al., 2018a; Teo & Chia, 2018; Sofian Suhaimi et al., 2021;

Teo et al., 2020; Zheng et al., 2020; Suhaimi et al., 2021). EEG appears to be more effective at representing emotional responses sent to the brain, especially for devices with more channels (Bin Suhaimi et al., 2020). EEG data are currently collected using wearable devices such as the Muse EEG headband (Saganowski et al., 2020) and Cognionics (Casciola et al., 2021), which makes it easier for researchers to get a brain response to the emotions stimulated by the material (e.g., video, figure) shown. Wearable EEGs are considered low-cost, non-invasive devices for monitoring brain activity during daily activities (Abujelala et al., 2016; Garcia-Moreno et al., 2020). As a result, the budget required is relatively small compared to the use of complex medical EEGs, and the user does not experience any restrictions on their freedom of movement. Hence, it suits various measurement needs, including usability tests on game products or virtual reality interfaces. These criteria make EEG data collected with portable EEG headbands the top choice for Southeast Asian researchers in building real-time emotion detection models.

The main alternative to other types of data that researchers use in the Southeast Asia area is data related to heart rate (HR), which is converted from photoplethysmography (PPG) data that measures blood volume pulse (BVP), and skin conductivity, which is represented in Galvanic Skin Response (GSR). Several studies have combined these two types of data, which are simultaneously collected by the same wearable device, such as the Empatica E4 wristband (Dao & Kasem, 2018; Bulagang et al., 2021b;), Shimmer3 (Huynh et al., 2016), and Xiaomi Miband 1S (Le-Quang et al., 2019). A researcher may be able to obtain more material for feature extraction and selection by using two types of data collected using one device. It has been shown that HR and GSR data can be used as a companion to more complicated EEG data based on results obtained in emotion detection studies. The use and analysis of HR and GSR are generally more straightforward, particularly during the pre-processing and integration phases of the process (Saganowski et al., 2020), in contrast to EEG data, which requires the selection of channels, the filtering phase and the removal of artifacts (Al-Nafjan et al., 2017). In other words, understanding EEG data requires considerably more skill and understanding than HR or GSR data.

Other types of data that are rarely collected are data obtained from smartphones, such as human facial data (Ramos et al., 2018; Ujir et al., 2021), human voices (Razali et al., 2023), subjective ratings based on emotion surveys (Liliana et al., 2021), and comments typed by smartphone users (Wahyono et al., 2022). Research using this data type has been initiated with devices that are relatively easy to obtain and do not require a large budget. The use of this data is compatible with being used to detect emotions in daily activities and is carried out outside the conditioning laboratory.

Regarding the size of the participants involved, the use of EEG data tends to require a larger number of participants ranging from 10 to 31 participants (Huynh et al., 2016; Suhaimi et al., 2018a; Teo & Chia, 2018) compared to HR and GSR which involve around 4-25 participants in their research (Huynh et al., 2016; Md Ali et al., 2017; Nguyen et al., 2017; Dao & Kasem, 2018; Le-Quang et al., 2019; Bulagang et al., 2020, 2022). The number of devices used in the collection of data as well as the sample rate used, also play a role in determining the number of participants required. The sample rate is also a benchmark for determining the duration of data collection. For EEG data, the duration of data collection ranged from 10 seconds to 12 minutes, while for HR and GSR, it ranged from 8 minutes to 7 days. The wristband or smartwatch allows participants to collect data on HR and GSR outside the laboratory for a longer period than the wearable EEG. A summary of how researchers in Southeast Asia select the type of data, the devices used, and the scale of the participants involved can be seen in.

3.2. Analysis method and classification performance

The analytical method applied by researchers in Southeast Asia in the process of classifying participants' emotional status is dominated by machine learning classifiers such as RF (Huynh et al., 2016; Bin Suhaimi et al., 2020; Suhaimi et al., 2021; Teo et al., 2020), DT (Huynh et al., 2016; Nguyen et al., 2017), Logistic Regression (LR) based method, e.g., PHASOR-system (Dao & Kasem, 2018), SVM (Huynh et al., 2016; Md Ali et al., 2017; Nguyen et al., 2017; Dao & Kasem, 2018; Le-Quang et al., 2019; Suhaimi et al., 2020; Bulagang et al., 2020, 2021a;), NB (Ramli et al., 2018; Bin Suhaimi et al., 2020;), K-Nearest Neighbor (KNN) (Nguyen et al., 2017; Suhaimi et al., 2020; Bulagang et al., 2022; Wahyono et al., 2022), and the Gradient Boosting Machine (GBM) (Bin Suhaimi et al., 2020). Some researchers also use deep learning methods such as basic Artificial Neural Networks (ANN) (Dao & Kasem, 2018; Suhaimi et al., 2021) and DNN (Teo & Chia, 2018). Deep learning methods are used primarily for studies with massive amounts of data involving a minimum of 15 to 31 participants. It confirms that deep learning methods' sensitivity is inadequate for classification cases with relatively small data sets (Najafabadi et al., 2015; Koppe et al., 2020). In addition to these two types of methods, some researchers also apply more traditional statistical methods such as the Local Binary Pattern Histogram (Ramos et al., 2018) and Certainty Factor (Liliana et al., 2021).

Each study carried out the emotional status classification with various emotional classes. Some researchers use degrees of arousal-valence levels. Generally, this degree is divided into four quadrants of Russel's emotions (Saganowski et al., 2020), namely, high arousal with positive valence (HA-PV), which represents happy emotions, low arousal with positive valence (LA-PV), which represents feelings of calm, high arousal with negative valence (HA-NV) which represents feelings of anger, and low arousal with negative valence (LA-NV) which represents feelings of boredom (Bulagang et al., 2020, 2021a, 2021c, 2021b, 2022). In addition, the classification of emotions is also carried out using categorical emotion levels that directly describe the feelings or emotions of participants.

Table 1. List of data selection, participant size, duration of data collection, and wearable devices used by Southeast Asian researchers in emotion detection research

No.	Author(s)	Country	Participant size	Collected data	Duration of collection	Device
1	Huynh, et al. (2016)	Singapore	22	GSR, PPG, EEG	12 minutes	Shimmer3 device integrated with Jasper system; Emotive Epoc+
2	Nguyen, et al. (2017)	Vietnam	5	HR	30-180 s	Android-based application built into a smartphone
3	Minhad, et al. (2017)	Malaysia	25	Electrodermal activity (EDA)	25 minutes	Built-in Grove EDA sensor in an Arduino Uno-based devices
4	Ramli, et al. (2018)	Malaysia	-	Voice	7 hours	Photographic Affection Meter application installed on a smartphone
5	Ramos, et al. (2018)	Phillipines	20	Face image	15 minutes	Smartphone camera
6	Dao, et al. (2018)	Brunei	15	Body temperature, BVP, accelerometer, and Electrodermal activity (EDA).	7 days	Empatica E4 wristband
7	Suhaimi, et al. (2018)	Malaysia	10	EEG	10 seconds	Muse Headband
8	Teo, J., & Chia, J. T. (2018)	Malaysia	24	EEG	10 seconds	Muse Headband
9	Le-Quang, et al. (2019)	Brunei	4	HR and EDA	NA	Xiaomi Miband 1S
10	Suhaimi, et al. (2020)	Malaysia	31	EEG	320 seconds	Muse Headband
11	Le-Quang, et al. (2020)	Brunei	31	EEG	320 seconds	Muse 2016 EEG headset
12	Suhaimi, et al. (2020)	Malaysia	31	EEG	320 seconds	Muse EEG Headset
13	Bulagang, et al. (2020)	Malaysia	10	HR	320 seconds	Empatica E4 wristband
14	Liliana, et al. (2021)	Indonesia	26	Subjective rating	NA	EmoHealth application installed on a smartphone
15	Ujir, et al. (2021)	Malaysia	20	Face image (eye, nose, and mouth area)	Every 40 seconds along a 45-mile driving distance.	Mobile phone camera installed with developed classification app.
16	Bulagang, et al. (2021)	Malaysia	10	EDA	405 seconds	Empatica E4 wristband
17	Bulagang, et al. (2021)	Malaysia	24	HR and inter-beat interval	6 minutes	Empatica E4 wristband
18	Bulagang, et al. (2021)	Malaysia	10	HR and EDA	1,464 seconds	Empatica E4 wristband

Table 1. (cont.')

No.	Author(s)	Country	Participant size	Collected data	Duration of collection	Device
19	Suhaimi,et al. (2021)	Malaysia	31	EEG	350 seconds	Muse 2016 EEG headset
20	Suhaimi, et al. (2021)	Malaysia	31	EEG	320 seconds	Muse 2016 EEG headset
21	Wahyono, et al. (2022)	Indonesia	-	Text	3 months	SIPEJAR application installed on the smartphone
22	Bulagang, et al. (2022)	Malaysia	5	HR and EDA	1,464 seconds	Empatica E4 wristband

These levels encompassed angry, happy, bored, calm, afraid, sad, disappointed, excited, alert, stressed, depressed, disgusted, neutral, and confused. (Huynh et al., 2016; Md Ali et al., 2017; Nguyen et al., 2017; Ramli et al., 2018; Ramos et al., 2018; Dao and Kasem, 2018; Le-Quang et al., 2019; Bin Suhaimi et al., 2020; Teo et al., 2020; Liliana et al., 2021; Wahyono et al., 2022). In emotion detection research, assessment surveys using SAM, PANAS, and questionnaires from the International affective picture system or IAPS (Saganowski et al., 2020). However, in research in Southeast Asia, the method of collecting participants' emotional status has not been clearly stated, especially for those who employ a non-categorical classification system. In the classification of categorical emotional status, researchers used a survey that was developed in a systematic manner that included categorical types of emotions (Bin Suhaimi et al., 2020; Teo et al., 2020; Liliana et al., 2021).

Regarding the type of emotional level used, research using a categorical system tends to produce less accurate results than research using the emotional quadrant system. The level of accuracy for categorical systems ranges from 25% to 93% for machine learning methods and 99% for deep learning methods. High accuracy was found in studies involving at least 15 participants. In studies using the emotional quadrant system, the accuracy obtained ranged from 50% to more than 99% accuracy. However, these results need to be reviewed in light of the data labeling process, which is not explained in detail. In brief, the summary of the classification method, emotional level system, and classification performance from emotion detection research in Southeast Asia in the last decade is presented in.

3.3. Experimental procedure and methods

The review of the procedure and methods applied in the experiments results in three main ideas. The ideas comprise the participant's position when doing the task(s), whether the participant wore the device during data collection, and the environmental condition during the experiment. The experimenter set these criteria based on the objective of their research.

Emotion detection research has primarily been conducted in seated conditions (Huynh et al., 2016; Md Ali et al., 2017; Ramos et al., 2018; Le-Quang et al., 2019; Ujir et al., 2021). This fact is true both for research using wearable devices and not. For example, data collection using wearable EEG (Huynh et al., 2016), GSR or EDA (Utami et al., 2019), and body temperature (Dao & Kasem, 2018). Standing positions were set up more in VR-based research (Suhaimi et al., 2018a, 2021).

Regarding the environmental condition, the experiment can be done in the lab with conditioned conditions, e.g., temperature, lighting, and screen illuminance. This environment is especially set for development research instead of applied research. For example, Suhaimi et al. (2018a, 2021) and Huynh et al. (2016) conducted experiments aimed at usability tests on VR and the gaming field. Different from Dao et al. (2018) and Le-Quang et al. (2019), who researched emotion detection applied to students in the classroom. This kind of research did not require a conditioned environment to test the detection accuracy in real conditions. Based on the reviews, the majority of emotion detection research in Southeast Asian countries was still conducted in the development stage instead of applied states. Therefore, in the future, applied research needs to be more promoted around researchers in Southeast Asian countries. The summary of reviews on experimental procedures and methods is shown in Table 3.

3.4. Potency for emotion detection research in South-East Asia

Based on the literature search results obtained in this review, the opportunities for research into emotion detection in Southeast Asia are still very broad. Most research over the past ten years has been conducted in Malaysia (14 out of 22) with a variety of authors who are still homogeneous. Other countries such as Singapore, Indonesia, and Thailand have significant potential to participate in conducting research in this field. In addition, multi-national research is also an opportunity for researchers in the Southeast Asian region.

Regarding the type of data taken, it can be more beneficial to utilize data taken from smartphones, such as accelerometers, gyroscopes, and voices. This is because the costs of these devices are relatively affordable and easy to operate. Other physiological data that can be considered is eye movement, consisting of data on pupil diameter, fixation duration, saccades, and features related to eye blinking. Research in other regions has tested the ability of eye movement features to be used in building emotion detection models (Alghowinem *et al.*, 2013; Krithika & Priya, 2016).

Table 2. List of classification methods, emotional state leveling systems, and classification performance produced by Southeast Asian researchers in emotion detection research over the past decade

No.	Author(s)	Country	Emotion states	Analysis methods	Classification performance
1	Huynh, et al. (2016)	Singapore	Excitement, happiness, frustration, amusement.	SVM, DT (J48), RF	70.83-77.38 of emotion classification accuracy.
2	Nguyen, et al. (2017)	Vietnam	Fear, anger, sadness, disgust, neutral, happiness	KNN, SVM, DT	The accuracy of KNN, SVM, and decision tree are 61%, 79%, and 52%, respectively.
3	Minhad, et al. (2017)	Malaysia	Neutral, happy, angry, recovery.	SVM	40%-76% of accuracy
4	Ramli, et al. (2018)	Malaysia	Angry, sad, happy, neutral	NB	46-65% of accuracy rate.
5	Ramos, et al. (2018)	Phillipines	Engage, frustration, confusion, boredom, surprise, sadness, happiness, fear, disgust, contempt, anger, and neutral.	Fisherfaces, Local Binary Pattern Histogram, and Eigenfaces	The accuracy of Fisherfaces, Local Binary Pattern Histogram, and Eigenfaces are 47.93%, 26.90%, and 25.16%, respectively.
6	Dao, et al. (2018)	Brunei	Alert, excited, elated, happy, content, serene, relaxed, calm, fatigued, bored, depressed, sad, upset, stressed, nervous, and tense.	SVM, J48, ANN, LR using PHASOR-system	57.3%-65.2% of emotions detection accuracy
7	Suhaimi, et al. (2018)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	KNN and SVM.	Both KNN and SVM methods resulted in an 82.4% of accuracy average.
8	Teo, J., & Chia, J. T. (2018)	Malaysia	Neutral, excitement.	DNN	69.71%-99.07% of accuracy.
9	Le-Quang, et al. (2019)	Brunei	Neutral, positive, negative.	SVM	93.81% of accuracy average
10	Suhaimi, et al. (2020)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	KNN, SVM, deep learning.	SVM reaches the best accuracy, 85.01%
11	Suhaimi, et al. (2020)	Malaysia	Happy, angry, boring, and calm	Distributed Random Forest (DRF), GBM and NB	DRF, GBM, and NB obtained classification accuracy of 82.49%, 67.04%, and 36.24%, respectively.
12	Teo, et al. (2020)	Malaysia	Happy, upset, bored, relaxed	RF	86.20% of accuracy.
13	Bulagang, et al. (2020)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	SVM	53.39% of inter-subject accuracy and 56.92%-86.15% of intra-subject accuracy.
14	Liliana, et al. (2021)	Indonesia	Happy, sad, angry, fear	Certainty Factor	92.31% of accuracy rate

Table 2. (cont.')

No.	Author(s)	Country	Emotion states	Analysis methods	Classification performance
15	Ujir, et al. (2021)	Malaysia	Angry, sleepy, and head posing.	Microsoft Azure Cognitive API	96.66%, 82.2, and 85.67% of anger, drowsiness, and head posing detection accuracy, respectively.
16	Bulagang, et al. (2021)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	SVM	54.3%-99.2% of accuracy.
17	Bulagang, et al. (2021)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	SVM	67.4%-100% of accuracy.
18	Bulagang, et al. (2021)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	SVM	66.0% of accuracy average
19	Suhaimi,et al. (2021)	Malaysia	Happy, scared, bored, and calm	Feedforward ANN	70.74% of accuracy average.
20	Suhaimi, et al. (2021)	Malaysia	Scared, happy, bored, calm.	RF	76.50% for intra-subject classification accuracy.
21	Wahyono, et al. (2022)	Indonesia	Happy, afraid, angry	KNN	0.697 of accuracy, 0.560 recall, and 0.442 precision
22	Bulagang, et al. (2022)	Malaysia	HA/PV, LA/PV, HA/NV, LA/NV.	KNN	97.7% of accuracy.

Table 3. List of experimental procedures and methods produced by Southeast Asian researchers in emotion detection research over the past decade

No.	Author(s)	Country	Participant Position	Controlled Environment	Worn Device Utilization
1	Huynh, et al. (2016)	Singapore	Sitting	Yes	Yes
2	Nguyen, et al. (2017)	Vietnam	Sitting in front of a television screen.	Yes	No
3	Ramos, et al. (2018)	Phillipines	Sitting in front of a computer screen.	Yes	No
4	Dao, et al. (2018)	Brunei	Sitting in the classroom.	No	Yes
5	Suhaimi, et al. (2018)	Malaysia	Standing.	Yes	Yes
6	Teo, J., & Chia, J. T. (2018)	Malaysia	Standing.	Yes	Yes
7	Le-Quang, et al. (2019)	Brunei	Sitting in the classroom.	No	Yes
8	Liliana, et al. (2021)	Indonesia	Moving.	No	No
9	Ujir, et al. (2021)	Malaysia	Sitting on the car seat.	Yes	No
10	Suhaimi,et al. (2021)	Malaysia	Standing	Yes	Yes
11	Suhaimi, et al. (2021)	Malaysia	Standing	Yes	Yes

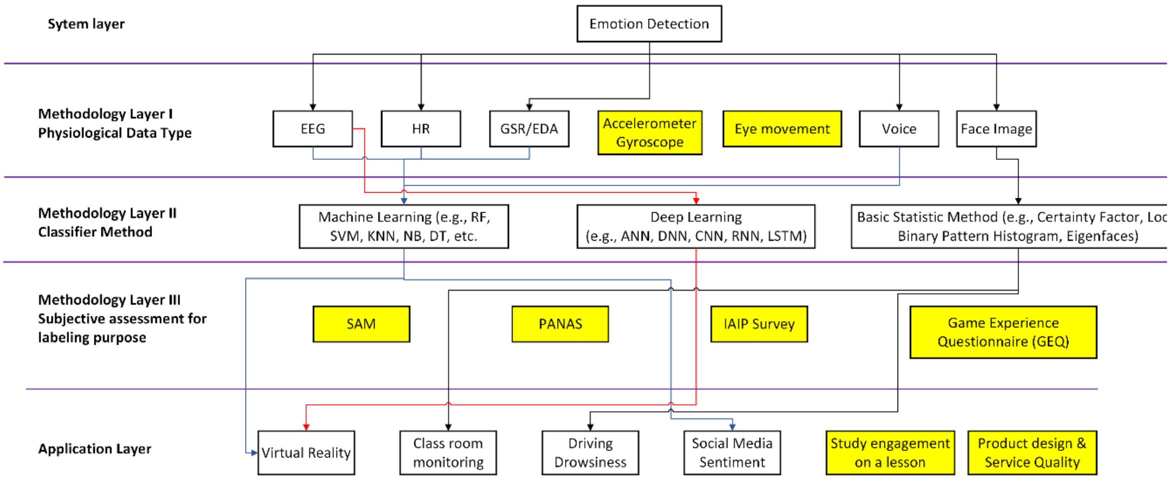


Figure 3. K-Chart shows the development of emotion detection research in Southeast Asia over the past decade. Future research opportunities are indicated by sections with a yellow background

There are various AI modeling methods that have been applied to this field. Most of them using machine learning methods comprising RF, SVM, KNN, NB, and DT. Deep learning methods that are useful to be applied are ANN, CNN, DNN, RNN, and LSTM. However, in the area of Human Factors, it is recommended to use machine learning methods instead of deep learning methods. The characteristics of deep learning that has the ability to do self-features engineering (O'Brien *et al.*, 2018; Banan *et al.*, 2020) become a limitation in the Human Factors field. Human Factors scientist has the responsibility for understanding each feature processing process and is unsuitable with deep learning's black box process (O'Brien *et al.*, 2018).

Most of the detection applications are carried out in the realm of VR interface design and games. Other applications such as the detection of emotions related to driving (Nakisa *et al.*, 2018), monitoring student attitudes in a classroom (Dao & Kasem, 2018), measuring study engagement related to the level of difficulty of the lesson (Maier *et al.*, 2019), product design (Yadollahi *et al.*, 2017), and also responses to service quality (Alsaggaf & Althonayan, 2018; Jain *et al.*, 2018) can be alternative applications. Regarding the feature extraction process, it is still limited to using raw data (Bulagang *et al.*, 2021b, 2022) compared to generating features independently, such as using a time domain approach (Kamdar & Wu, 2016; Schmidt *et al.*, 2018), frequency (Gupta *et al.*, 2016; Jalilifard *et al.*, 2017), statistical properties (Rattanyu *et al.*, 2010; Guo *et al.*, 2015), or complexity analysis (Nakisa *et al.*, 2018; Zhao *et al.*, 2018).

A lack of clarity about how participant emotional status data are collected can be used to improve research on emotion detection in Southeast Asia. To maintain the validity of data labeling, capturing participant emotions is essential (Akçay & Oğuz, 2020; Saganowski *et al.*, 2020). Therefore, a subjective emotional status measurement tool with international recognition should be used to ensure the validity of data entered by participants. As previously explained, the recommended questionnaires include SAM, PANAS, and questionnaires from the International affective picture system or IAPS (Saganowski *et al.*, 2020). The K-Chart shown in Figure 3 briefly illustrates these research novelty opportunities, especially with the yellow background elements.

4. CONCLUSION

A systematic review of research on emotion detection using wearable devices carried out in Southeast Asian countries has resulted in the understanding that most of this research is still being conducted in Malaysia with homogeneous authors. This study involved 5-31 participants, depending on the research stage. For research at an early stage, relatively smaller-size subjects were employed. EEG, HR, EDA/GSR, and voice and facial data are collected. These data were collected using wearable devices such as Muse headbands, Empatica E4, Shimmer 3, smartphones, and Emohealth. The methods used for classification are variations between machine learning, deep learning, and traditional statistical methods. This classification results in accuracy that varies from 25% to close to 99%.

In addition, through this review, it was also found that in the data labeling process, many researchers had not used the internationally recommended subjective assessment tool. Therefore, in the future, researchers hope to apply emotional status surveys that have been tested for validity. As a result, physiological data can be labeled more precisely. It is possible to develop this review by examining the feature engineering process that can be used to develop real-time emotion detection models. An appropriate feature engineering process can result in a more robust detection model.

REFERENCES

Abdullah, M. K., Mohd Suradi, N. R., Jamaluddin, N., Mokhtar, A. S., Abu Talib, A. R., & Zainuddin, M. F. (2006). K-chart: a tool for research planning and monitoring. *Journal of Quality Management And Analysis*, *2*(1), 123–130.

Abujelala, M., Abellanoza, C., Sharma, A., & Makedon, F. (2016). Brain-ee: Brain enjoyment evaluation using commercial eeg headband. *Proceedings of the 9th Acm International Conference on Pervasive Technologies Related to Assistive Environments*, 1–5.

Akçay, M. B., & Oğuz, K. (2020). Speech emotion recognition: Emotional models, databases, features, preprocessing methods, supporting modalities, and classifiers. *Speech Communication*, *116*, 56–76.

Al-Nafjan, A., Hosny, M., Al-Ohali, Y., & Al-Wabil, A. (2017). Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review. *Applied Sciences*, *7*(12), Article 1239.

Alghowinem, S., Goecke, R., Wagner, M., Parker, G., & Breakspear, M. (2013). Eye movement analysis for depression detection. *2013 IEEE International Conference on Image Processing*, 4220–4224.

Alsaggaf, M. A., & Althonayan, A. (2018). An empirical investigation of customer intentions influenced by service quality using the mediation of emotional and cognitive responses. *Journal of Enterprise Information Management*, *31*(1), 194–223.

Banan, A., Nasiri, A., & Taheri-Garavand, A. (2020). Deep learning-based appearance features extraction for automated carp species identification. *Aquacultural Engineering*, *89*, Article 102053.

Bin Suhaimi, N. S., Mountstephens, J., & Teo, J. (2020). Emotional State Classification with Distributed Random Forest, Gradient Boosting Machine, and Naïve Bayes in Virtual Reality Using Wearable Electroencephalography and Inertial Sensing. *ISCAIE 2020 - IEEE 10th Symposium on Computer Applications and Industrial Electronics*, 12–17.

Bulagang, A. F., Mountstephens, J., & Teo, J. (2021a). A Novel Approach for Emotion Classification in Virtual Reality using Heart Rate (HR) and Inter-beat Interval (IBI). *2021 IEEE International Conference on Computing, ICOCO 2021*, 247–252.

Bulagang, A. F., Mountstephens, J., & Teo, J. (2021b). Electrodermography and Heart Rate Sensing for Multiclass Emotion Prediction in Virtual Reality: A Preliminary Investigation. *2021 IEEE Symposium on Industrial Electronics and Applications, ISIEA 2021*.

Bulagang, A. F., Mountstephens, J., & Teo, J. (2021c). Support Vector Machine Tuning for Improving Four-Quadrant Emotion Prediction in Virtual Reality (VR) using Wearable Electrodermography (EDG). *Journal of Physics: Conference Series*, *1878*(1), Article 012020.

Bulagang, A. F., Mountstephens, J., & Teo, J. (2022). Investigating Electrodermography (EDG) and Heart Rate (HR) Signals for Emotion Classification in Virtual Reality. *IVIT 2022 - Proceedings of 1st International Visualization, Informatics and Technology Conference*, 29–34.

Bulagang, A. F., Mountstephens, J., & Wi, J. T. T. (2020). Tuning Support Vector Machines for Improving Four-Class Emotion Classification in Virtual Reality (VR) using Heart Rate Features. *Journal of Physics: Conference Series*, *1529*(5), Article 052069.

Casciola, A. A., Carlucci, S. K., Kent, B. A., Punch, A. M., Muszynski, M. A., Zhou, D., Kazemi, A., Mirian, M. S., Valerio, J., & McKeown, M. J. (2021). A deep learning strategy for automatic sleep staging based on two-channel EEG headband data. *Sensors*, *21*(10), Article 3316.

Dao, M.-S., Dang-Nguyen, D.-T., & Kasem, A. (2018). HealthyClassroom-a proof-of-concept study for discovering students' daily moods and classroom emotions to enhance a learning-teaching process using heterogeneous sensors. *Proceedings of the 7th International Conference on Pattern Recognition Applications and Methods, 1*, 685-691.

Dzedzickis, A., Kaklauskas, A., & Bucinskas, V. (2020). Human Emotion Recognition: Review of Sensors and Methods. *Sensors, 20*(3), 592.

Feng, H., Golshan, H. M., & Mahoor, M. H. (2018). A wavelet-based approach to emotion classification using EDA signals. *Expert Systems with Applications*, *112*, 77–86.

Fernández-Aguilar, L., Martínez-Rodrigo, A., Moncho-Bogani, J., Fernández-Caballero, A., & Latorre, J. M. (2019). Emotion detection in aging adults through continuous monitoring of electro-dermal activity and heart-rate variability. *Understanding the Brain Function and Emotions: 8th International Work-Conference on the Interplay Between Natural and Artificial Computation, IWINAC 2019, Almería, Spain, June 3–7, 2019, Proceedings, Part I 8*, 252–261.

Garcia-Moreno, F. M., Bermudez-Edo, M., Rodríguez-Fórtiz, M. J., & Garrido, J. L. (2020). A CNN-LSTM deep Learning classifier for motor imagery EEG detection using a low-invasive and low-Cost BCI headband. *2020 16th International Conference on Intelligent Environments (IE)*, 84–91.

Godfrey, A., Hetherington, V., Shum, H., Bonato, P., Lovell, N. H., & Stuart, S. (2018). From A to Z: Wearable technology explained. *Maturitas*, *113*, 40–47.

Gonzalez, H. A., Muzaffar, S., Yoo, J., & Elfadel, I. M. (2020). BioCNN: A Hardware Inference Engine for EEG-Based Emotion Detection. *IEEE Access*, *8*, 140896–140914.

Guo, H. W., Huang, Y. S., Chien, J. C., & Shieh, J. S. (2015). Short-term analysis of heart rate variability for emotion recognition via a wearable ECG device. *2015 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, 262–265.

Gupta, R., Khomami Abadi, M., Cárdenes Cabré, J. A., Morreale, F., Falk, T. H., & Sebe, N. (2016). A quality adaptive multimodal affect recognition system for user-centric multimedia indexing. *Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval*, 317–320.

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews*, *18*(2), Article 1230.

Hartono, M. (2020). The modified Kansei Engineering-based application for sustainable service design. *International Journal of Industrial Ergonomics*, *79*, Article 102985.

Huynh, S., Lee, Y., Park, T., & Balan, R. K. (2016). Jasper: Sensing gamers' emotions using physiological sensors. *MobiGames 2016 - Proceedings of the 3rd Workshop on Mobile Gaming, Co-Located with MobiSys 2016*, 1–6.

Jaharuddin, N. S., & Zainol, L. N. (2019). The Impact of Work-Life Balance on Job Engagement and Turnover Intention. *The South East Asian Journal of Management*, *13*(1), Article 7.

Jain, S., Jain, V., & Das, S. (2018). Relationship analysis between emotional intelligence and service quality with special evidences from Indian banking sector. *Revista Espacios*, *39*(33), Article 3.

Jalilifard, A., da Silva, A. G., & Islam, M. K. (2017). Brain-tv connection: Toward establishing emotional connection with smart tvs. *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, 726–729.

Kadariya, S., Gautam, R., & Aro, A. R. (2019). Physical Activity, Mental Health, and Wellbeing among Older Adults in South and Southeast Asia: A Scoping Review. *BioMed Research International*, *2019*, Article 6752182.

Kamdar, M. R., & Wu, M. J. (2016). PRISM: a data-driven platform for monitoring mental health. *Biocomputing 2016: Proceedings of the Pacific Symposium*, 333–344.

Kanjo, E., Younis, E. M. G., & Ang, C. S. (2019). Deep learning analysis of mobile physiological, environmental, and location sensor data for emotion detection. *Information Fusion*, *49*, 46–56.

Koppe, G., Meyer-Lindenberg, A., & Durstewitz, D. (2020). Deep learning for small and big data in psychiatry. *Neuropsychopharmacology*, *46*(1), 176–190.

Krithika, L. B., & Priya, G. G. L. (2016). Student emotion recognition system (SERS) for e-learning improvement based on learner concentration metric. *Procedia Computer Science*, *85*, 767–776.

Le-Quang, B. L., Dao, M.-S., & Nazmudeen, M. S. H. (2019). Wemotion: A system to detect emotion using wristbands and smartphones. In *Communications in Computer and Information Science*, *968*, 92–103.

Liliana, D. Y., Ismail, I. E., Zain, A. R., & Balgis, S. S. (2021). Emotion Intelligent Application for Independent Wellbeing Management using Certainty Factor. *Proceedings - 2021 4th International Conference on Computer and Informatics Engineering: IT-Based Digital Industrial Innovation for the Welfare of Society, IC2IE 2021*, 338–343.

Lu, X., Liu, X., & Stolterman Bergqvist, E. (2019). " It sounds like she is sad" Introducing a Biosensing Prototype that Transforms Emotions into Real-time Music and Facilitates Social Interaction. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–6.

Maier, M., Elsner, D., Marouane, C., Zehnle, M., & Fuchs, C. (2019). DeepFlow: Detecting Optimal User Experience From Physiological Data Using Deep Neural Networks. *AAMAS*, 2108–2110.

Minhad, K. N., Ooi, J. S. K., Md Ali, S. H., Reaz, M. I., & Ahmad, S. A. (2017). Low-cost wearable sensor for human emotion recognition using skin conductance response. *IEICE Transactions on Information and Systems*, *E100D*(12), 3010–3017.

Mullins, J. T., & White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics*, *68*, 102240.

Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. *Journal of Big Data*, *2*(1), 1–21.

Nakisa, B., Rastgoo, M. N., Rakotonirainy, A., Maire, F., & Chandran, V. (2018). Long short term memory hyperparameter optimization for a neural network-based emotion recognition framework. *IEEE Access*, *6*, 49325–49338.

Naruetharadhol, P., & Gebsombut, N. (2020). A bibliometric analysis of food tourism studies in Southeast Asia. *Cogent Business & Management*, *7*(1), Article 1733829.

Nguyen, N. T., Nguyen, N. V, Tran, M. H. T., & Nguyen, B. T. (2017). A potential approach for emotion prediction using heart rate signals. *Proceedings - 2017 9th International Conference on Knowledge and Systems Engineering*, 221–226.

Noelke, C., McGovern, M., Corsi, D. J., Jimenez, M. P., Stern, A., Wing, I. S., & Berkman, L. (2016). Increasing ambient temperature reduces emotional well-being. *Environmental Research*, *151*, 124–129.

O'Brien, N., Latessa, S., Evangelopoulos, G., & Boix, X. (2018). *The language of fake news: Opening the black-box of deep learning-based detectors*. https://dspace.mit.edu/handle/1721.1/120056

Pollreisz, D., & TaheriNejad, N. (2017). A simple algorithm for emotion recognition using physiological signals of a smart watch. *2017 39th Annual International Conference of the Ieee Engineering in Medicine and Biology Society (EMBC)*, 2353–2356.

Prabowo, D. S. P., & Aji, H. M. (2021). Visual packaging and perceived emotional value: A study on Islamic branded cosmetics. *The South East Asian Journal of Management*, *15*(1), Article 4.

Ramli, I., Jamil, N., Ardi, N., & Hamzah, R. (2018). Emolah: A Malay language spontaneous speech emotion recognition on iOS platform. *International Journal of Engineering and Technology(UAE)*, *7*(3), 151–156.

Ramos, A. L. A., Flor, J. M., Casabuena, M. M., & Estrada, J. E. (2018). Face expression extraction using eigenfaces, fisherfaces, and local binary pattern histogram towards predictive analysis of students emotion in programming. In *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering*, *248*, 38–46.

Rattanyu, K., Ohkura, M., & Mizukawa, M. (2010). Emotion monitoring from physiological signals for service robots in the living space. *ICCAS 2010*, 580–583.

Razali, N. A. M., Malizan, N. A., Hasbullah, N. A., Wook, M., Zainuddin, N. M., Ishak, K. K., Ramli, S., & Sukardi, S. (2023). Political Security, Threat Prediction Framework, Using Hybrid Lexicon-Based Approach and Machine Learning Technique. *IEEE Access*, *11*, 17151–17164.

Saganowski, S., Dutkowiak, A., Dziadek, A., Dzieżyc, M., Komoszyńska, J., Michalska, W., Polak, A., Ujma, M., & Kazienko, P. (2020). Emotion recognition using wearables: A systematic literature review-work-in-progress. *2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, 1–6.

Schmidt, P., Reiss, A., Duerichen, R., Marberger, C., & Van Laerhoven, K. (2018). Introducing Wesad, a multimodal dataset for wearable stress and affect detection. *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, 400–408.

Sofian Suhaimi, N., Mountstephens, J., & Teo, J. (2021). Class-Based Analysis of Russell's Four-Quadrant Emotion Prediction in Virtual Reality using Multi-Layer Feedforward ANNs. *ACM International Conference Proceeding Series*, 155–161.

Suhaimi, N. S., Mountstephens, J., & Teo, J. (2020). Parameter tuning for enhancing inter-subject emotion classification in four classes for vr-eeg predictive analytics. *International Journal of Advanced Science and Technology*, *29*(6 Special Issue), 1483–1491.

Suhaimi, N. S., Mountstephens, J., & Teo, J. (2021). Explorations of A Real-Time VR Emotion Prediction System Using Wearable Brain-Computer Interfacing. *Journal of Physics: Conference Series*, *2129*(1).

Suhaimi, N. S., Teo, J., & Mountstephens, J. (2018a). Emotional State Classification in Virtual Reality Using Wearable Electroencephalography. *IOP Conference Series: Materials Science and Engineering*, *341*(1).

Suhaimi, N. S., Teo, J., & Mountstephens, J. (2018b). Empirical analysis of intra vs. Inter-subject variability in VR EEG-based emotion modeling. *Journal of Engineering and Applied Sciences*, *13*(8), 2137–2144.

Teo, J., & Chia, J. T. (2018). Deep Neural Classifiers for Eeg-Based Emotion Recognition in Immersive Environments. *2018 International Conference on Smart Computing and Electronic Enterprise, ICSCEE 2018*.

Teo, J., Suhaimi, N. S., & Mountstephens, J. (2020). Pushing the boundaries of EEG-based emotion classification using consumer-grade wearable brain-computer interfacing devices and ensemble classifiers. *International Journal of Advanced Science and Technology*, *29*(6 Special Issue), 1475–1482.

Ujir, H., Jee, E. M., Farhaan Iqbal, M., Mun, Q. K., & Hipiny, I. (2021). Real-Time Driver's Monitoring Mobile Application through Head Pose, Drowsiness, and Angry Detection. *Proceedings of the 8th International Conference on Computer and Communication Engineering, ICCCE 2021*, 1–6.

Utami, K., Rauf, A., & Salmiah, S. (2019). Consumer Behavior Analysis in Organic Vegetables Decision Making in Medan City. *Agrotekma: Jurnal Agroteknologi Dan Ilmu Pertanian*, *3*(2), 75.

Valliappan, S., Mohan, B. P. R., & Kumar, S. R. (2017). Design of low-cost, wearable remote health monitoring and alert system for elderly heart patients. *2017 International Conference on IoT and Application (ICIOT)*, 1–7.

Wahyono, I. D., Saryono, D., Putranto, H., Asfani, K., Rosyid, H. A., Sunarti, Mohamad, M. M., Said, M. N. H. B. M., Horng, G. J., & Shih, J.-S. (2022). Emotion Detection based on Column Comments in Material of Online Learning using Artificial Intelligence. *International Journal of Interactive Mobile Technologies*, *16*(3), 82–91.

Xu, T., Yin, R., Shu, L., & Xu, X. (2019). Emotion recognition using frontal EEG in VR affective scenes. *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*, *1*, 1–4.

Yadollahi, A., Shahraki, A. G., & Zaiane, O. R. (2017). Current state of text sentiment analysis from opinion to emotion mining. *ACM Computing Surveys (CSUR)*, *50*(2), 1–33.

Yang, B., Li, X., Hou, Y., Meier, A., Cheng, X., Choi, J.-H., Wang, F., Wang, H., Wagner, A., & Yan, D. (2020). Non-invasive (non-contact) measurements of human thermal physiology signals and thermal comfort/discomfort poses-a review. *Energy and Buildings*, *224*, 110261.

Zaheer, S., Amjad, M. S., Rafique, M. Z., & Khan, M. A. (2020). A K-Chart-based implementation framework to attain lean & agile manufacturing. *International Journal of Production Management and Engineering*, *8*(2), 123–135.

Zhao, B., Wang, Z., Yu, Z., & Guo, B. (2018). EmotionSense: Emotion recognition based on wearable wristband. *2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, 346–355.

Zheng, L. J., Mountstephens, J., & Teo, J. (2020). Comparing eye-tracking versus EEG features for four-class emotion classification in VR predictive analytics. *International Journal of Advanced Science and Technology*, *29*(6 Special Issue), 1492–1497.