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PSYMed: Detecting Panic Attack Precursors Using a Convolutional Neural Network-based Facial Expression Recognition Model

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The thesis, entitled **“PSYMed: Detecting Panic Attack Precursors Using a Convolutional Neural Network-based Facial Expression Recognition Model”** prepared and submitted by Group 23-CS-002 consisted of **Ria Millicent A. Cordero, John Joshua C. Mesia, and Angelie Badar** in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Science** is hereby accepted.

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, 5^{th} Edition
FER	Facial Expression Recognition
FER-CNN	Facial Expression Recognition-Convolutional Neural Network
PAPCA	Panic Attack Precursor Classification Algorithm

ARTICLE 1

PSYMed: Detecting Panic Attack Precursors Using A Convolutional Neural Network-Based Facial Expression Recognition Model

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Abstract

Panic attacks, characterized by intense fear and various physiological symptoms, have become more prevalent amid the COVID-19 pandemic, which has caused significant psychological distress globally. In the Philippines, seeking mental health treatment remains a challenge due to stigmatization and limited access to services. To address these issues to provide accessible mental health care services to underserved areas, this study explores the development of a Facial Expression Recognition Convolutional Neural Network (FER-CNN) model that is capable of recognizing panic attack precursors through facial expressions. Using a combination of FER2013, MMAFEDB, and a modified, light version of FER-AffectNet for the dataset, and the VGG-16 CNN model, the model has achieved an overall performance rating of 66.86%. Moreover, the model excels in real-world scenarios, particularly under optimal conditions such as a well-lit environment and high frame-rate cameras. The findings highlight the potential of machine learning technologies, particularly in computer vision, in mental health diagnosis, offering valuable insights to both psychological professionals and remote therapy seekers.

Keywords: Convolutional Neural nNetworks, facial expression recognition, panic attacks, mental health, computer vision, machine learning

SDGs: Goal 3 (Good Health and Mental Well-being), Goal 10 (Reduced Inequalities)

1. Introduction

Panic attacks are abrupt episodes of intense fear that occur due to existing phobias. A few of the common patterns in panic attacks, as described in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), are accelerated heart rate or palpitations, trembling or shaking, sweating, paranoia, agitated or shortness of breathing, light-headedness, numbness, chills, or heat sensations, derealization or detachment from reality, fear of losing control or going crazy, and fear of dying. Identifying these patterns early on will help psychologists recognize an impending panic attack (American Psychiatric Association, 2013). Experiencing panic attacks also does not immediately imply the presence of a mental health disorder, such as major depressive disorder (MDD), anxiety disorder, or post-traumatic stress disorder. Nonetheless, it may serve as an indicator for such conditions. However, the recurrence of unexpected panic attacks can be classified as a panic disorder (Valdes et al., 2021).

In recent years, the panic attack phenomenon has become more prevalent most especially during the COVID-19 pandemic. Searches for panic-attack-related terms, such as “anxiety,” “panic attack,” and “insomnia,” have grown significantly during the beginning of the COVID phenomenon, specifically in March 2020, when statewide lockdowns were being implemented. This has remained 18% higher than anticipated for the following three weeks and the term “panic attack” has specifically soared up to 56% higher than usual during the initial weeks of lockdown. This has brought a huge amount of psychological distress among individuals across the globe (Stijelja & Mishara, 2020). However, amid these psychological distresses, Filipinos all over the world display reluctance and unfavorable attitudes towards seeking help in managing symptoms of mental disorders. This is most likely caused by financial barriers, self, and social stigmatization of seeking psychological treatments, and most notably, inaccessibility of mental health services. It is also noted that Filipinos who reside in foreign countries show reluctance towards seeking treatment due to the same barriers in addition to the lack of health insurance, language barrier, discrimination, and lack of acculturation (Martinez et al., 2020). Despite the importance of this matter, the budget for the provision of comprehensive mental health services in the country remains poorly resourced, allotting only 3-5% of the total health budget to mental healthcare provisions. In addition to this, underdeveloped communities remain to be unreached by these said services. These prohibitive conditions in the Philippine economy and the inaccessibility of these services contribute to the Filipinos' limited access to mental healthcare (Lally et al., 2019). The compounding factors of financial barriers, stigma associated with seeking help for mental health issues, and limited access to mental health services further exacerbate the emotional struggles faced by Filipinos. The reluctance to seek assistance due to concerns about cost, societal judgment, and lack of available resources only deepens the psychological burden. As a result, individuals may find it challenging to manage their anxiety and fear effectively, leading to a cycle of decreased work productivity, further intensifying stress, and potentially worsening mental health conditions (Law-ay, 2022).

The reliance on technology has significantly increased during the COVID-19 pandemic. There has been a rapid transition from in-person healthcare to approaches that were enabled by technology. This enabled patients to receive care without the risk of exposure to the virus, which is critical especially among patients with chronic conditions

(Mehrotra et al., 2020). In the context of mental healthcare, considering that inaccessibility is a huge factor toward the minimal availing of mental healthcare services, providing services through telemedicine is something that is being considered due to its availability and accessibility (Yuduang et al., 2022). Telemedicine applications have enabled patients to consult their doctors through long-distance appointments enabled by phone or video technologies. In a mental healthcare setup, discussing fears and phobias by the patients can help psychologists identify any psychological and biological factors that may be contributing to the distressing situations of a patient, providing them with different ways to manage or overcome them. However, triggering panic attacks during these sessions is inevitable as they trigger specific physical reactions without real danger, and the lack of constant interaction and direct monitoring of the patients due to the limitations of technology makes it difficult for doctors to meet their patients' psychological demands (Markina, 2021).

Therefore, by taking the typical patterns of panic attacks, this study intends to develop a Convolutional Neural Network (CNN) model that can recognize behavioral patterns manifesting through facial expressions and classify them as panic attacks.

CNNs are deep learning algorithms within the Artificial Neural Network (ANN) class commonly used for analyzing and processing input data, usually for image classification. CNNs use convolutional layers to learn spatial patterns and representations of the input data hierarchy to reduce the features' dimensionality (Bengio & Courville, 2016). With the development of the algorithm, this study also aims to:

1. Create a dataset containing the facial expressions of a panic attack by consolidating the FER2013 dataset with similar facial image datasets such as the MMAFEDB and AffectNet.
2. Train a Convolutional Neural Network model in recognizing and classifying facial expression patterns associated with panic attacks and evaluate its effectiveness.
3. Test the effectiveness of the FER-CNN model through a real-world software application in detecting panic attack precursors.

The proposed study is targeted towards underserved areas in the Davao region, specifically in the municipality of Sto. Tomas, Davao del Norte, due to the lack of mental healthcare facilities and professionals in the area. The municipality of Sto. Tomas as per the 2022 census ~~has~~ a 135,370 total population across all 19 barangays. Currently, the mental health program developed by the local government unit (LGU) of Sto. Tomas allows them to hire a psychologist from Davao City to conduct monthly consultations. However, due to the limited availability of the hired psychologist, the program can only be conducted once every month. Upon interviewing the locale's head of municipal health office, they stated that they would have preferred to have a mental health facility with an in-house psychologist since all patients from the second district of Davao del Norte only rely on the program they are conducting. However, this is made impossible by their lack of budget. In conducting the study, the researchers aim to conduct applied research among the residents of the municipality aged 18 to 25 years old.

The study has the potential to provide insights into panic attack patterns and advance the understanding of different underlying mechanisms relating to panic attacks and other similar mental health conditions. By utilizing various computational technologies and algorithms, specifically machine learning, this study aims to contribute to the healthcare field by paving the way to develop tools to assist in the diagnosis of mental health disorder symptoms. Once the study is concluded, the gathered results and data can benefit psychological professionals and individuals who are seeking remote access to therapy, irrespective of their location. Furthermore, the findings of this study can also serve as a valuable point of reference for researchers who intend to conduct a similar study.

2. Related Works

This section reviews related studies that aid in providing a comprehensive overview of the study within the existing academic discourse, particularly in the themes of the nature of panic attacks, CNN applications in health care and facial emotion recognition, and modern technologies in telemedicine. By reviewing these related studies, the researchers aim to identify the gaps in existing pieces of related literature, set the parameters to be considered in conducting the study, such as different methods and techniques used in other related works, and critically synthesize all relevant studies to formulate a stronger foundation for this thesis.

2.1. Nature of Panic Attacks

To date, the most recent definition of panic attacks is provided by the American Psychiatric Association (2013), in which panic attacks are an abrupt onset of intense fear and extreme discomfort, occurring from a calm or an anxious state, that peaks within minutes. Symptoms of a panic attack can be classified as physical or cognitive. Physical symptoms include accelerated heart rate or palpitations, trembling or shaking, sweating, paranoia, agitation or shortness of breathing, light-headedness, numbness, and chills or heat sensations. Whereas cognitive symptoms include derealization or detachment from reality, fear of losing control or going crazy, and fear of dying. Having panic attacks also does not immediately assume that a person has a mental health disorder, such as major depressive disorder (MDD), anxiety disorder, or post-traumatic stress disorder, but it could be an indicator for one. However, the recurrence of unexpected panic attacks can be classified as a panic disorder (Valdes et al., 2021). The differences in the symptoms of a person having infrequent panic attacks are insignificant to those whose panic attacks occur more frequently.

In contrast to the existing pieces of literature that thoroughly describes the experience of having a panic attack among adults, there is not much literature pertaining to panic attacks among adolescents. ~~H~~ewitt et al. (2021) explored the lived experiences of adolescents, aged 14 to 18 years old, in an interpretative-phenomenological analysis. Six superordinate themes were derived from the study, which reflected the intense nature of a panic attack from the perspective of the age group targeted in this study. The superordinate themes include: the use of natural disaster as a metaphor for panic attacks, disconnection from the self in the occurrence of a panic attack, feeling out of control over one's mental abilities, affected identity, disconnection, and isolation from others, and finding ways to cope. The findings were consistent with the cognitive model of panic attacks among adults. However, it is also noted that despite having a close similarity with panic attacks among adults, the lack of discussion towards this matter among adolescents might have been caused by their inability to seek treatments or the service requirements that prohibit them from availing these treatments due to their lack of experienced symptoms. Furthermore, it is noted in this study that the clinical treatments that are provided for adolescents should be tailored to their developmental stage.

Panic attacks can be provoked by modern computing technologies. In a study by Freire et al. (2019), the researchers explored computer simulations and exposure to virtual reality as a technique for the research and treatment of panic disorder. The study has asserted that the provided computer simulation and virtual reality exposure is a stimulus that can provoke a panic attack among patients diagnosed with panic disorder with agoraphobia (PDA). The computer simulations used in the study successfully demonstrated the objectives, inducing panic attack symptoms such as anxiety and hyperventilation, among the PDA patients but not among the healthy subjects. The computer simulation exposure posed similar levels of panic attack induction as an in vivo exposure (directly facing a feared object), and respiratory and caffeine challenges. This study opens a possibility for computing technologies as a provocative and predictive approach to identifying and treating panic attacks.

In parallel to these related works identified above, a study by Lang (1995), it is described that human emotion is not random but is rather driven by two opposing motivational systems: appetitive and aversive. The appetitive system pertains to the attraction to pleasant experiences, while the aversive system repels humans from unpleasant experiences. The study also highlights how human reactions vary based on affective psycho-physiologies, defined by valence—appetitive/pleasant or aversive/unpleasant— and arousal levels. The human emotion described by Lang in his paper intersects Lang’s insights on the motivational systems of emotions with the nature of panic attacks: the interplay between the appetitive and aversive circuits of a human emotion or reaction underpins the paradoxical nature of panic attacks, where intense fear coexists with intense physiological arousal. Lang's framework suggests that this paradox can be defined by the opposing motivational systems discussed earlier. In simpler terms, the reaction of humans to certain experiences during panic attacks is influenced by how pleasant and unpleasant the emotions are and the intensity of their emotional response.

2.2. Convolutional Neural Networks in Facial Expression Recognition

Convolutional Neural Networks, as described in Chapter 2.2, are highly used in image processing applications. Thus, it is an effective algorithm for describing and classifying facial emotion patterns on still and moving images. A few examples include Facial Expression Recognition (FER) using CNN and SoftMax function on Captured Images (Deopa et al., 2019), and FER Using a Deep Convolutional Neural Network by (Pranav et al., 2020). These studies incorporated CNNs in analyzing facial emotion patterns.

CNN were used to categorize each labeled grayscale facial image from a large dataset into seven human emotion categories. The activation function used in this paper is the SoftMax function, a sigmoid function used to classify the data into seven classes. The trained model could detect emotions on still images and live image streams outside the dataset captured using a web camera (Deopa et al., 2019). In a similar study, a deep CNN was used to classify input images in 32x32 size into five classes of human emotions (angry, happy, neutral, sad, and surprised). DCNN modifies the traditional CNN by using two convolutional layers with dropouts after each layer. The output from the first layer, the feature map, is passed through the Rectified Linear Unit (ReLU) activation function and then to a pooling layer. The process is again repeated for the output, producing another convolution layer output (Pranav et al., 2020).

In five different approaches, Kartali et al. (2018) conducted a comparative study for real-time facial emotion recognition of four basic emotions (anger, sadness, happiness, and fear). The study compared three different deep-learning approaches using CNNC, alongside two conventional approaches for classifying Histogram of Oriented Gradients (HOG) features. The five different approaches are the following: commercial Affdex CNN solution, AlexNet CNN, custom-made FER-CNN, Multilayer Perceptron (MLP) artificial neural network of HOG features, and Support Vector Machine (SVM) of HOG features. A total of 8 volunteers (5 female and 3 male) performed the real-time testing wherein they had to express the four different emotions. Moreover, in the comparison of the results of the different approaches used, the proponents simultaneously test all the proposed algorithms in real time using identical input data. The gathered results of real-time testing are shown in the form of confusion matrices and based on the results, Affdex CNN achieved the highest accuracy of 85.05% followed by AlexNet, with the accuracy of 76.64%. In line with this, SVM and AlexNet have better “anger” recognition with an accuracy of 96.77% than the Commercial Affdex CNN (70.97%). While FER-CNN demonstrates the least overall accuracy, it exhibits notable precision in recognizing emotions associated with “sadness”, akin to the Affdex CNN result (81.82% vs 84.85%).

In the study of Zahara et al. (2020), facial emotion recognition in real-time was proposed by employing the CNN algorithm with Raspberry Pi. This approach involved predicting and recognizing micro-expressions through feature extraction. The proponents utilized an OpenCV library named Keras and TensorFlow. Moreover, the design and testing of facial microexpression systems encompass two main stages: 1) the Training Process and 2) the Testing Process. In the data training process, the proponents utilized the FER-2013 dataset which has been pre-processed using the CNN algorithm to generate feature extraction that will be evaluated with data validation. On the other hand, the testing process is carried out in real time using a tool for image input (webcam) and the Haar Cascade Classifier method, a feature module for detecting facial objects. Based on the results, the utilization of the CNN architectural model in the facial expression detection system could be effectively achieved in real time with optimal performance. In line with this, the outcomes of facial expression prediction in the study using the CNN technique using the Facial Emotion Recognition (FER-2013) dataset yielded an accuracy rate of 65.97%.

The Deep Convolutional Neural Network was utilized in the proposed method by Liliana (2021) in emotion recognition. The study offers two novelty and contributions to the domain of FER: (1) Automated process for feature extraction by utilizing a CNN based on deep learning to identify the occurrence of Action Units and (2) Utilized CK+ dataset, setting apart from earlier studies that relied on SEMAINE and BP4D. In using CNN for FER, there are two convolutional layers (the first layer uses six masks, and the second layer uses 12 masks) and two subsampling layers. It has been observed in the conducted experiment that an increase in the quantity of training data leads to a reduction in the mean square error, while the mean square error correlates linearly with the number of testing data points. For the entire testing, 92.81% was achieved wherein the lowest accuracy rate is the anger class with 87.73% and the highest one is the surprise class with 98.09%.

Badrulhisham and Mangshor (2021) proposed a mobile application designed for real-time emotion recognition through facial expressions. The CNN is implemented in this study for recognizing the emotion and the MobileNet algorithm is utilized to train the model for recognition. In line with this, the task involves identifying four distinct facial expressions: sadness, happiness, surprise, and disgust. Moreover, to enhance the image used for the training process, the proponents used the argumentation process in the Roboflow platform. An analysis was also performed during the training process to determine the most suitable and optimal ratio for splitting images into separate sets for training, testing, and validation. As for the result, the ideal and optimal ratio for splitting images is 90% for training images, and 5% each for both testing and validation images. Furthermore, the proponents successfully developed the emotion recognition application, attaining an accuracy rate of 92.50% for both sensitivity and specificity, with sensitivity at 85% and specificity at 95%.

In the study of Singh and Nasoz (2020), CNN were utilized to showcase the classification of FER using static images, eliminating the need for pre-processing in feature extraction. The dataset used in this study is the FER2013. In line with the model's training of the study, Singh and Nasoz used six convolutional layers with RELU as an activation function. The optimal test accuracy was determined through experimentation with various batch sizes and epochs. The batch size of 512 and 10 epochs achieved the best test accuracy which resulted in a 61.7% accuracy rate without any pre-processing and feature extraction techniques. In addition, the study discusses further techniques for improving the accuracy rate of FER2013 which includes the pre-processing and feature extraction techniques.

Gan (2018) discussed the development of FER in different CNN architecture such as residual neural network (ResNet), GoogleNet, visual geometry group network (VGGNet), and AlexNet using the FER2013 dataset. The study also explores two categories of feature extraction, namely the extraction of geometric features and a technique grounded in comprehensive statistical characteristics. In utilizing the FER2013 dataset in different CNN architectures, five epochs were used which are 25, 20, 12, 8, and 6. It was noted that the accuracy increased in VGGNet and AlexNet during epochs 25 to 20 and ResNet maintained an average accuracy rate of 55 to 60 percent, signifying a favorable outcome. However, in training the model, overfitting happened which implies that the final accuracy cannot be solely determined based on the number of epochs. Moreover, based on the results of accuracy using different CNN architectures, AlexNet achieved the highest among all the architectures with a 64.24% accuracy rate (epochs = 20 and lrate = 0.001).

Manewa and Mayurathan (2020) achieved an accuracy rate of 64.56% in their study, which centers on the recognition and differentiation of facial expressions through the application of CNN. The study introduces a novel approach for FER that goes ahead with Deep Learning principles, focusing on CNN utilizing the TensorFlow and Keras backend framework. As for assessing the effectiveness of the proposed methodology, a challenging FER 2013 dataset was used. The detection and classification of emotion and user awareness based on emotions are the two major aspects that were addressed in this study. The proposed approach includes convolutional layers, separable convolutional layers, dense layers, both max pooling and global average pooling layers, batch normalization functions, dropout layers, and activation functions using SoftMax and RELU. Following the classification stage, the objective shifts to surveillance based on the emotions of anger and fear. It is revealed that the emotions of fear and anger could potentially stem from the same neurotransmitter, and both emotions contribute to the perception of threats.

The study of Liu (2019) conducted a comparison of deep convolutional neural networks architectures such as AlexNet, VGG16, VGG19, ResNet152, and their own proposed network in recognizing facial expression. The FER2013 dataset was used in training the convolutional neural network. The proposed deep convolutional neural network structure of Liu is composed of 12 layers, there are two (2) convolutional layers, three (3) ReLU layers, two (2) max pooling layers, three (3) full connection layers, and two (2) batch normalization layers. Different batch sizes were used in training the model and different accuracies were achieved. The final test accuracy of the proposed network achieved 49.8% which is higher than the other methods. AlexNet, VGG16, VGG19, and ResNet152 achieved 15.2%, 37.4%, 39.68%, and 48.67% respectively.

A multimodal facial biometric system called IdentiFace was developed by Rabea et al. (2024) using VGG16 architecture. The IdentiFace application is a combination of multiple biometric traits such as face shape, gender, and emotion. Various datasets were utilized in different biometric traits including the FERET database for face recognition, a manually collected dataset (members of their own faculty consisted of 8 females and 15 males), and a popular gender recognition dataset for the gender classification, celebrity face shape data for predicting face shapes, and lastly, FER2013 dataset for the emotion recognition. By utilizing the VGGNet model, the recognition task attained an accuracy of 99.2% with the FERET database, 95.15% on the public dataset, and 99.4% on a manually collected dataset for gender recognition. Additionally, the model achieved an 88.03%

accuracy in predicting face shape and a 66.13% accuracy rate for emotion recognition using the FER2013 dataset, which is considered satisfactory.

2.3. Modern Technologies in Psychological Consultations

In recent years, the use of modern technology in clinician and patient consultation has impacted a lot in the field of medical care, and the landscape of psychological consultations has undergone a transformative shift, thanks to the integration of modern technologies. These technological advancements have not only redefined the ways in which mental health support is accessed and delivered but have also opened new avenues for individuals to engage with therapeutic interventions. From virtual therapy sessions to AI-driven chatbots, these modern tools are reshaping the field, offering enhanced accessibility, flexibility, and personalized approaches to mental well-being.

The cases of health consultations conducted in a telemedicine setup ~~have~~ significantly increased during the COVID-19 pandemic. In a study by Record et al. (2021) telemedicine can similarly mimic a traditional health visit by a patient to the clinic and it allows doctors to get a better characterization of the patient's individual life circumstances than possible in a traditional office visit. The use of, and experience with telemedicine have increased significantly during the COVID-19 pandemic. Patients and clinicians have high satisfaction because of the quality of communication and patient-centeredness and convenience factors including travel-related time and cost saving that contribute to this satisfaction.

A study by Roncero et al. (2020) described the response of the Mental Health Network of Salamanca in Spain to the COVID-19 pandemic, where their Psychiatry

Service needed to create a contingency plan and reorganize their resources in response to the situation, immediately within the first 8 weeks after the state of alarm was declared. The reorganization included the restructuring of human resources, closure of some psychiatric units, and the deployment of telemedicine programs, namely the mental health assistance program and another program for the homeless people of Salamanca. 9,038 phone call interviews were conducted with the outpatients of hospitals and community health programs, which decreased activity in subacute and acute hospital wards down to 50%. It was concluded that telemedicine is a promising tool to be used by any patient with any kind of disorder and that telemedicine can be implemented for daily practice in the future.

The exploration of computer-assisted therapy (CAT) is a subject of investigation in the modern age. It is usually based on evidence-based treatments, accessible online through the Internet, and may or may not be with embellishments of virtual environments intended to mimic a game environment. Currently, CATs are available as a national health service for countries like Australia, Netherlands, Great Britain, and India. CATs make assistance in psychological consultations a lot easier for mental health workers and expand treatments among underserved areas a lot more efficiently. When implemented as part of a treatment plan, CATs can be a powerful tool with the potential to enhance the provided care among patients and address physical barriers when providing care among patients residing in underserved territories (Dunne & Domakonda, 2019). In another study by Freire et al. (2019), which was also mentioned in Chapter 2.1, computer simulations and virtual reality technology have been used as a stimulus for assessing and treating panic disorder. The simulation was an effective approach to provoking a panic attack among patients with panic disorder with agoraphobia. The level of provocation matched those of in vivo exposure and respiratory and caffeine challenges.

A study by Heesacker et al. (2019) described the barriers to accessing college student mental health services, such as the cost, inadequate resources, failure to provide support among students seeking help, stigmatization, and premature termination. Computerizing treatments address these barriers by making health service applications available to download from the app store, and providing professional help by making information available, much quicker, and more convenient to access. Computerizing treatments also allowed students to seek help from a general practitioner rather than an actual therapist, reducing the stigmatization of their state, and the frequency of the use of electronic devices has become more common among college students, proving that students are most likely to remain active on their smartphone use to the point that it has become a habit. With the habitual use of technology among the younger generation, computer-assisted treatments have become more essential, with different technology-based approaches in addressing the barriers of seeking psychological help being opened for greater research and exploration.

Telemedicine is also being practiced in the national setting and was made popular during COVID-19 as well. A study by de Guzman et al. (2021) discussed that in the Philippines, the COVID-19 rules and regulations that were set during the lockdown restricted Filipinos aged below 21 years old and above 60 years old from leaving their homes. These age groups, however, are susceptible to various illnesses, whether it is related to the virus or not, which requires them to seek the medical care they need. Outpatient departments are mostly crowded, and distance was a crucial factor during the pandemic.

Thus, online healthcare systems have become more common to provide immediate care to patients without necessarily leaving their homes. The same study identified the telemedicine systems that were popular during the pandemic. This included the following: The Filipino Doctor, KonsultaMD, SeeYouDoc, Makati Medical Center, and iCliniq. Most of these telemedicine applications offer an automated hospital appointment system, a list of available doctors for consultation, e-prescription of medicine, and reviewing online medical records. Among these mentioned applications, only KonsultaMD offers health consultation through videoconferencing.

Videoconferencing technologies are now becoming more commonly available in telemedicine applications. A study by Matsumoto et al. (2018) assesses the feasibility of video conferencing as a medium for providing cognitive behavioral therapy (CBT) among remote patients with obsessive-compulsive disorder (OCD), panic disorder (PD), and social anxiety disorder (SAD). In this study, 30 patients received 16 sessions of video conference delivered internet-delivered cognitive behavioral therapy (ICBT) individually, conducted by a single therapist. 86% of these participants have stated their satisfaction with the ICBT session and 83% of the same population preferred ICBT over a face-to-face CBT session. It is also noted that an adverse event occurred to an SAD patient, which consists 3% of the population. In conclusion, conducting a video conference delivered CBT for patients with OCD, PD, and SAD, is feasible and acceptable.

However, in a commentary academic paper by Zargaran et al. (2020), the authors argued that the use of video conferencing tools alone is most likely insufficient to address the limitations on the scalability of the suggested therapy interventions. The authors also suggested that a combination of computer-assisted technologies (CBT) and video conferencing could be used to derive a new treatment regimen. In the Philippines, Cordero (2022) also argued that telemedicine, while being able to provide a range of benefits for both patients and healthcare providers, also has its limitations that deem it inapplicable in certain situations. The approach should only be availed on a case-by-case basis such as the physical incapacity to visit a medical facility for a checkup caused by distance and inability to travel long hours. A good telemedicine application should consider the internet connection strength and clear quality of equipment to be used. Thus, telemedicine, despite being an effective alternative, still cannot replace and guarantee to provide a high level of healthcare service provision like that of an in-person consultation.

To assess the effectiveness and usability of telemedicine applications, a mixed methods study by Noceda et al. (2023) was conducted about patient satisfaction with telemedicine utilization amid the COVID-19 pandemic. The study consisted of individuals between the ages of 18 and 65 living in the Philippines who had accessed telemedicine services throughout the COVID-19 pandemic. An online survey questionnaire was sent to the participants that encompassed socio-demographic characteristics and health-related expenditure. Additionally, the survey included inquiries drawn from two validated instruments: 15 questions from the Consumer Assessment of Healthcare Providers and Systems (CAHPS) Clinician & Group Adult Visit Survey 4.0, as well as 11 questions derived from the Telehealth Usability Questionnaire (TUQ). Based on the results, most of the participants express contentment with the telemedicine services offered amid the COVID-19 pandemic in terms of convenience, patient-physician relationship, communication, access, and cost. Among these factors, most participants (91.0%) chose convenience as it saved the time and effort of traveling to a hospital or specialized clinic.

Moreover, the participants have diverse perspectives regarding telemedicine, with some perceiving it as secure, effective, and efficient when barriers are removed. However, this was primarily the case for health issues that do not require physical examinations or laboratory tests.

This was also discussed in a study by Victor (2018), which describes that, while it is not a totally effective substitute for in-person medical service, telemedicine in the field of psychiatry is a validated and effective medical practice that increases accessibility to healthcare. Also known in terms like tele-mental health or e-mental health, telemedicine has provided psychiatric support and services across distances. It is crucial that nurses approach telemedicine technologies as a medium for providing healthcare services rather than a replacement tool for high-quality nursing practices. Telemedicine has been proven to be an effective supporting tool for mental healthcare services, but its ability to fully substitute in-person medical consultations is yet to be determined.

Psychological consultations are not only aided by various conferencing tools and software, but the technology also extends to wearable devices that improve the detection and monitoring of the said condition. Tsai et al. (2022) proposed a panic attack prediction model utilizing machine learning and wearable devices. A total of 59 participants took part in the study from En Chu Kong Hospital, Taiwan. The proposed panic attack prediction model utilized a dataset coming from environmental data, physiological data, and questionnaire data. The physiological data includes the data obtained from the smartwatch such as the participant’s beats per minute, distance traveled, different states, and many more. The data obtained from the smartwatch is being collected in real-time using the developed mobile app of the proponents. The questionnaire data involved mini international neuropsychiatric interview (MINI), beck anxiety inventory (BAI), panic disorder severity scale (PDSS), state-trait anxiety inventory (STAI), and beck depression inventory (BDI). In predicting PA's, different machine learning models were utilized such as decision trees, random forests, adaptive boosting (AdaBoost), linear discriminant analysis (LDA), regularized greedy forests (RGFs), and extreme gradient boosting (XGBoost). In the all-feature model, random forest achieved the highest accuracy among all the models, which is 81.3%, while XGBoost had the lowest accuracy, which is 67.4%. Nonetheless, the outcomes are only applicable to those patients diagnosed with PD, and further external testing is required.

Lazarou et al. (2022) developed panic detection utilizing machine learning and real-time biometric and spatiotemporal data. The study presents two objectives: to create a dataset containing both spatiotemporal and biometric data associated with detecting panic states in subjects engaged in various activities over a specified duration and to train the dataset using different machine learning models. The process of panic detection begins with the user wearing the wearable device, which tracks real-time biometric signals such as heart rate. Simultaneously, a smartphone application collects GPS location coordinates, speed, steps, and user activity. Moreover, in training the proposed dataset, among the seven classifiers, the Gaussian SVM classifier achieved the highest accuracy with an accuracy rate of 94.5%. This demonstrates the potential of utilizing machine learning in an effective panic detection system which can be expanded to accommodate multiple users, enabling the real-time identification of potential crowd panic incidents.

Panic attacks are characterized by the sudden onset of extreme fear and discomfort, with symptoms spreading into the physical and cognitive realms. Although this behavior is common among adults, it is relatively unknown among adolescents. Meanwhile, the emergence of CNNs in healthcare represents a paradigm shift. CNNs expertly interpret complex medical images, detecting problems such as cancers and skin diseases with surprising accuracy. This technological expertise extends to facial expression identification, in which CNNs detect emotional patterns in photographs ranging from basic to micro-expressions. Furthermore, similar technologies reverberate in psychological consultations, with video conferencing in telemedicine improving accessibility and computer-assisted therapy overcoming hurdles such as cost and stigma. This game-changing fusion of mental health and technology brings in a new era of comprehensive healthcare delivery.

3. Methods

3.1 Research Design

This study used an applied research design to address the problems identified in Chapter 1. The applied research design mainly focuses on developing the solution, in this case, the FER-CNN model, to be applied in a web application. The web application is used to capture and analyze data in real time through a web camera input. Three variables are displayed along with the camera input: valence level, arousal level, and emotion. Through this design, the researchers will determine whether the developed CNN model is an effective method in detecting panic attack precursors and can potentially improve the diagnosis of panic attack precursors by recognizing its facial cues when applied in a real-world setup.

3.2 Data Collection

As part of our research objectives, this study aims to create a dataset that can be used exclusively for identifying facial expression patterns of a panic attack. To enable this, the study made use of the Facial Expression Recognition 2013 (FER2013) dataset, combined with the MMAFEDB and a lighter version of the FER-AffectNet dataset, all of which are sourced from Kaggle and consists of images labeled with one of seven emotions: (1) anger, (2) disgust, (3) fear, (4) happiness, (5) sadness, (6) surprise, or (7) neutral. Additional emotions sourced from YouTube video frames and stock photos are processed using OpenCV and the Haar-Cascade model wherein the model automatically locates facial features and produces cropped-to-face (48x48) images. The emotions from these datasets are mapped according to the Valence-Arousal Circumplex (VAC) developed by Lang (1995), as described in Figure 2. The valence axis pertains to how pleasant and unpleasant the emotion is, denoted as positive and negative respectively. While the arousal axis pertains to its activation or intensity level (Wundt et al., 2018).

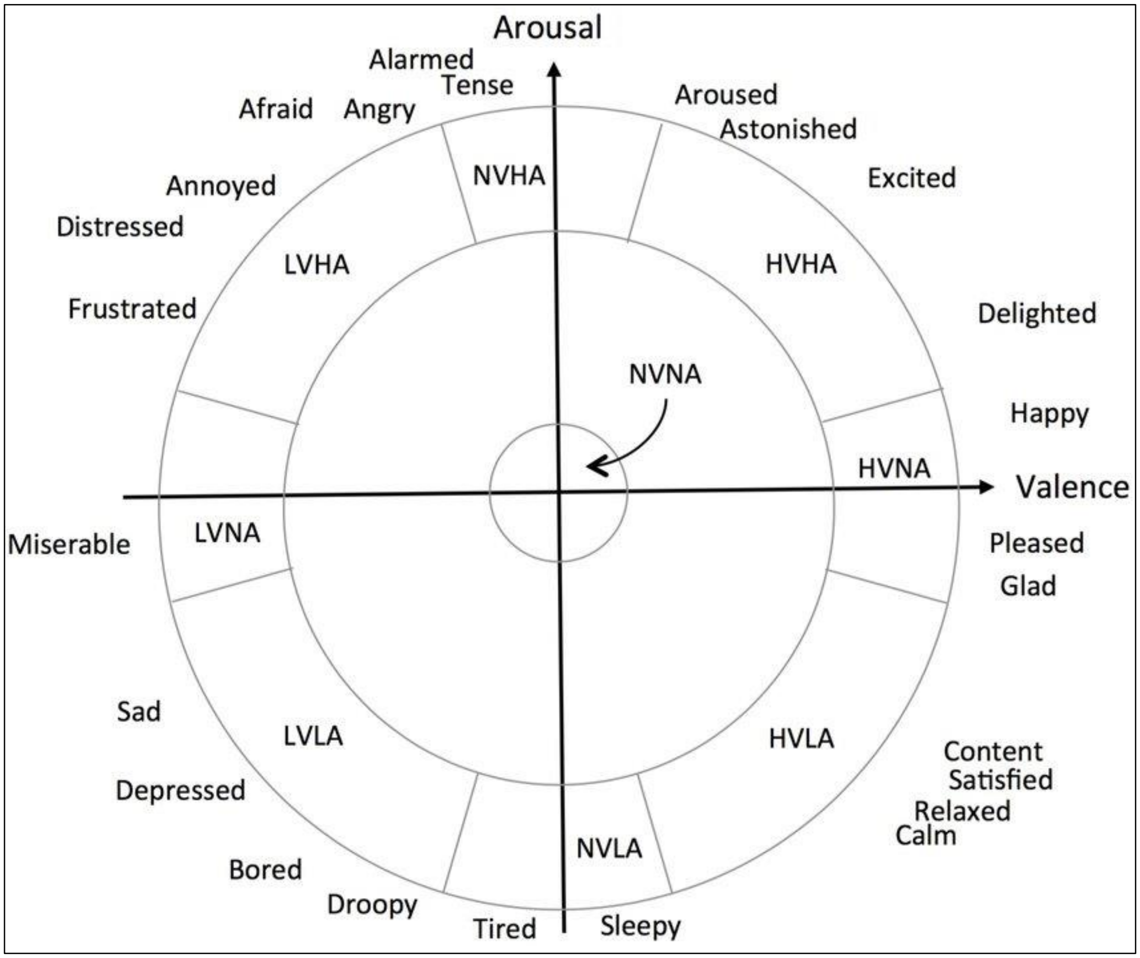


Fig. 1. Valence-Arousal Circumplex (Lang et al., 1995).

In this study, the circumplex served as the basis for mapping the valence-arousal levels of each emotion. Each emotion was assigned the following values based on their position on the VAC.

Table 1. Emotion to valence-arousal mapping table

Emotion	Valence Level	Arousal Level
Happy	0.8	0.6
Disgust	-0.6	-0.6
Fear	0.0	0.8
Angry	-0.8	0.8
Neutral	0.0	0.0
Sad	-0.8	0.6
Surprise	0.6	0.8

Predicting the valence-arousal values of emotions provided a more detailed understanding of emotional states compared to categorical labels. The continuous measures capture the intensity and nature of emotions, leading to a more fine-grained analysis and enabling the model to differentiate between subtle differences per emotional state.

3.3 Instrument

This study used the Python programming language and the TensorFlow library to train the CNN model. Python is widely used for machine learning applications due to its simplicity, flexibility, and availability of extensive libraries and resources. TensorFlow is an open-source machine learning framework by Google that is used to develop, train, and deploy machine learning models such as CNN. Both Python and TensorFlow have extensive documentation and an actively supportive community that can provide resources and support for the development phase of the CNN model. This study performed transfer learning from the VGG16 model, a method in which a pre-trained model is used as a starting point for training, leveraging the knowledge the model has already gained. Training the model using this method saves time and delivers more accurate results. The VGG16 model consists of 16 layers, hence, the name. Described in the table below is the overall structure of the model used in the study.

Table 2. VGG16 model architecture summary

Layer		Feature Map	Kernel Size	Stride	Activation
Input	Image	48x48x3	-	-	-
1	2x Conv	64	3x3	1	ReLU
	MaxPooling	64	24x24x64	2	ReLU
3	2x Conv	128	3x3	1	ReLU
	MaxPooling	128	12x12x128	2	ReLU
5	2x Conv	256	3x3	1	ReLU
	MaxPooling	256	6x6x256	2	ReLU
7	3x Conv	512	3x3	1	ReLU
	MaxPooling	512	3x3x512	2	ReLU
10	3x Conv	512	3x3	1	ReLU
	MaxPooling	512	1.5x1.5x512	2	ReLU
13	FC Layer	512	1x1x512	-	ReLU
14	FC Layer	512	1x1x512	-	ReLU
Output	FC Layer (Dense)	2	-	-	Linear

3.4 Data Analysis Plan

Data Pre-processing: A data annotation process was conducted to select images that show distress or intense emotions and can be identified as a panic attack. The images were selected from the FER2013 dataset and video frames captured from YouTube. The data labeling was based on the VAC described in Figure 2. This was validated by a group of psychologists. Once selected, the dataset has undergone pre-processing where they were resized and cropped to a desired dimension of 48x48 pixels. For this, an OpenCV and Haar-Cascade model was developed to automate the face detection and the resizing and cropping of the images. Since the VGG16 model requires images in RGB and the FER2013 dataset is grayscale by default, the images were converted from grayscale to RGB. MMAFEDB is in RGB format by default. Data augmentation techniques were used to expand the dataset by creating new augmented samples, increasing the diversity, and leading to better generalization. The processed and augmented data were used as input for a CNN model.

VGG16 Model and Panic Attack Precursor Classification Model: This study used the VGG16 pre-trained model for training the VAC mapping model. As detailed in Table 2, the model comprised a 48x48x3 input layer to represent the image. This involved a series of convolutional operations from the double convolutional layer with 64 feature maps. Each map utilized a 3x3 kernel and a stride level of 1. A ReLU layer is used as the activation layer. The output is down-sampled by a MaxPooling layer to 24x24x64 with a 2x2 kernel and ReLU activation function. This continued up until it has reached the final convolutional layer block consisting of dimensions of a 3x3x512-sized convolutional layer and a MaxPooling layer of 1.5x1.5x3. The fully connected (FC) layers consisted of two 512-unit dense layers with the ReLU as the activation function. The FC layers operated on a 1x1 feature map. The output layer is a dense layer with 2 units, designed for mapping the valence and arousal values in each captured facial expression. The mapped valence-arousal values were used to classify the panic attack emotions, as described in Figure 2.

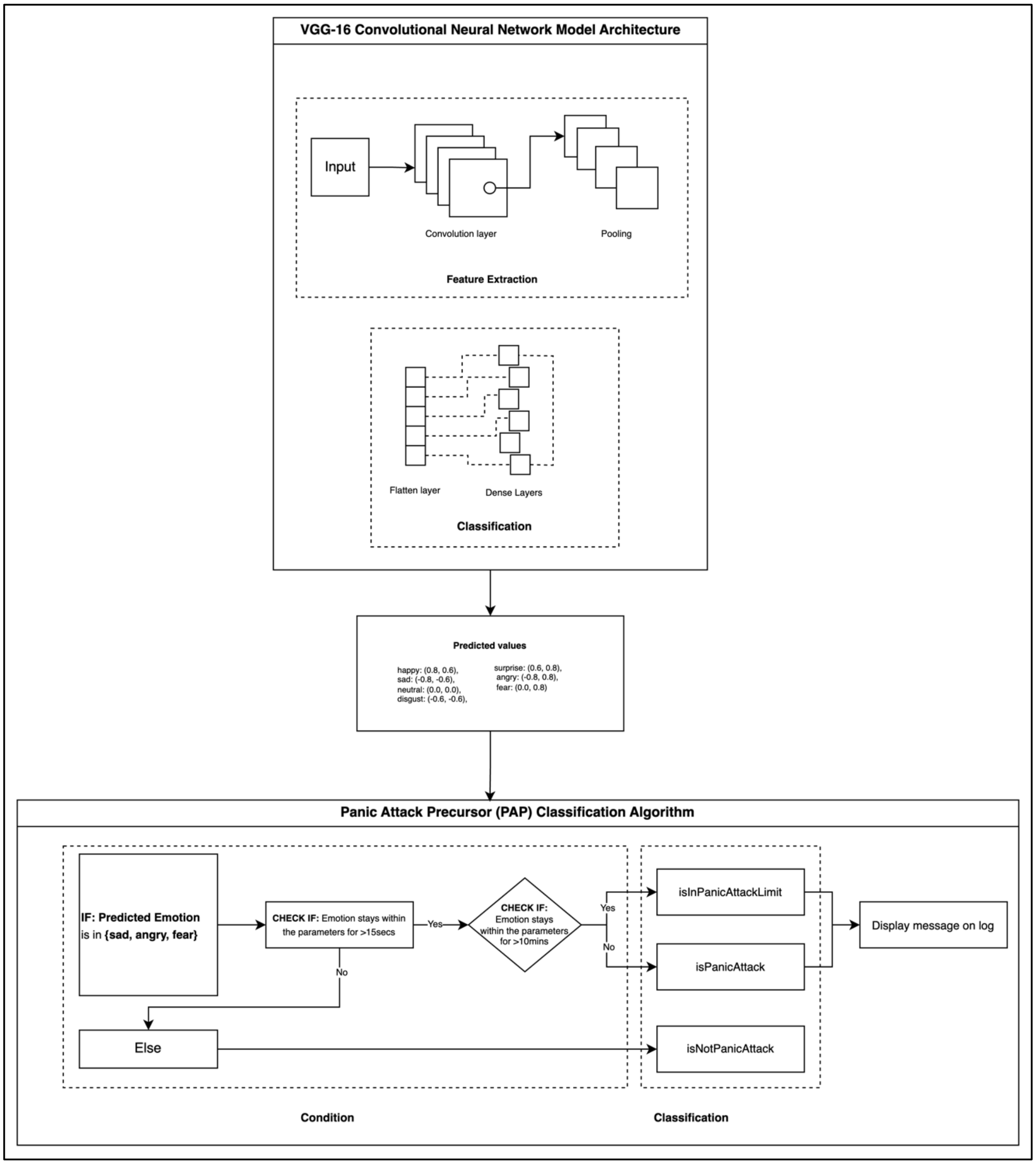


Fig. 2. FER-CNN Model for classifying panic attack precursors using the PAPCA

Model training and evaluation: The dataset was split into a training and testing set, with a distribution of 70% and 30% respectively. The training set was used to train the CNN model and the testing set was used to evaluate the model's performance. As a regression model, evaluation metrics such as loss rate, Mean Absolute Error, Mean Square Error, R2 Score, Explained Variance Score, and a scatterplot graph, were used to measure the performance of the developed CNN model. A regularization technique called early stopping was implemented to prevent overfitting by stopping the training process once the model performance has degraded or ceased to improve. Also, the learning rate of the model was set to decrease on its 40^{th} epoch and has further decreased after 20 more epochs. This was to optimize the model convergence.

Model interpretation: The dataset testing framework illustrated the process of the trained CNN model in recognizing the facial expression patterns of a panic attack in a human subject in real time. The model recognized patterns from a real-time video capture. However, due to ethical considerations, the developed model was intended to be tested in a simulated environment that closely mimics a telemedicine environment. In this case, this study created an environment where participants will play a horror or thriller game, with nyctophobia and horrifying images as the panic attack stimulus, while being recorded through a web camera. This served as a substitute for a telemedicine environment since it replicated the functionalities and interaction characteristics of a telemedicine application, where participants must be facing their laptop screen while being recorded by a web camera. This approach helped facilitate the systematic collection of data while providing a platform that emulates the real-world scenarios encountered in a telemedicine setup without having to collect sensitive information in a consultation.

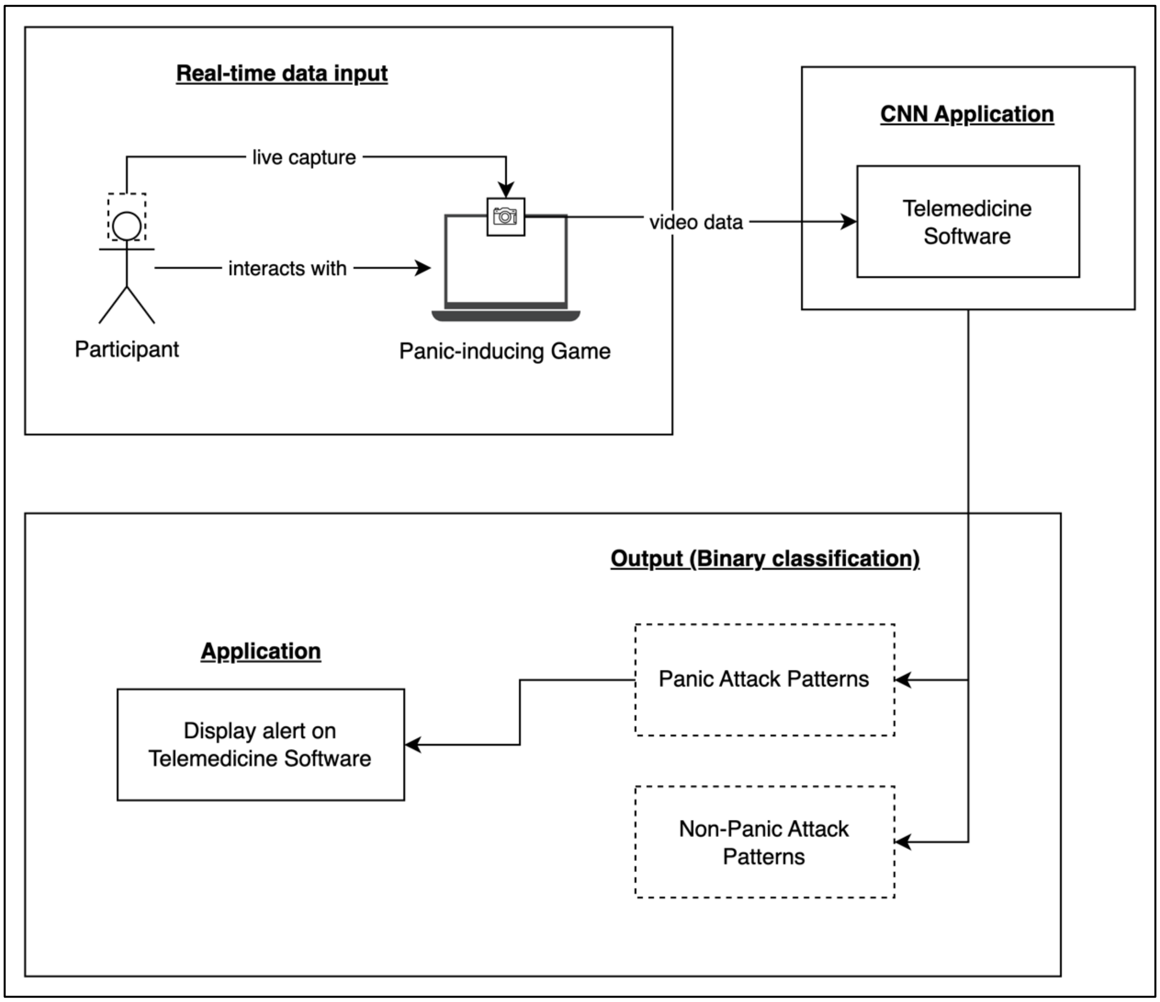


Fig. 3. FER-CNN Model real-world testing framework

The model training results were passed on to a Panic Attack Precursor Classification Algorithm (PAPCA) that is used to identify panic attack precursors from a recorded video or real-time camera input. Table 3 provided a summary of the rules that PAPCA is built around:

Table 3. Panic Attack Precursor Classification Algorithm rule summary

Rule No.	Parameters	Condition	Description
1	Predicted emotion	Belongs to sad, fearful, or angry	Emotions that identify with the stated condition are flagged as potential panic attack precursors
2	Emotions flagged as panic attack precursors	Stays within the parameters for >15secs	Flagged as panic attack precursors. Displays a message on the output log of the application
3	Panic attack precursors	Stays within the parameters for >600secs or 10 minutes	Displays message on output log recommending for specialists' intervention

Visualization: The developed model shall be applied in telemedicine software. Described in Figure 4 is the low-fidelity wireframe depicting how the user can navigate the telemedicine software.

3.5 Conceptual Framework

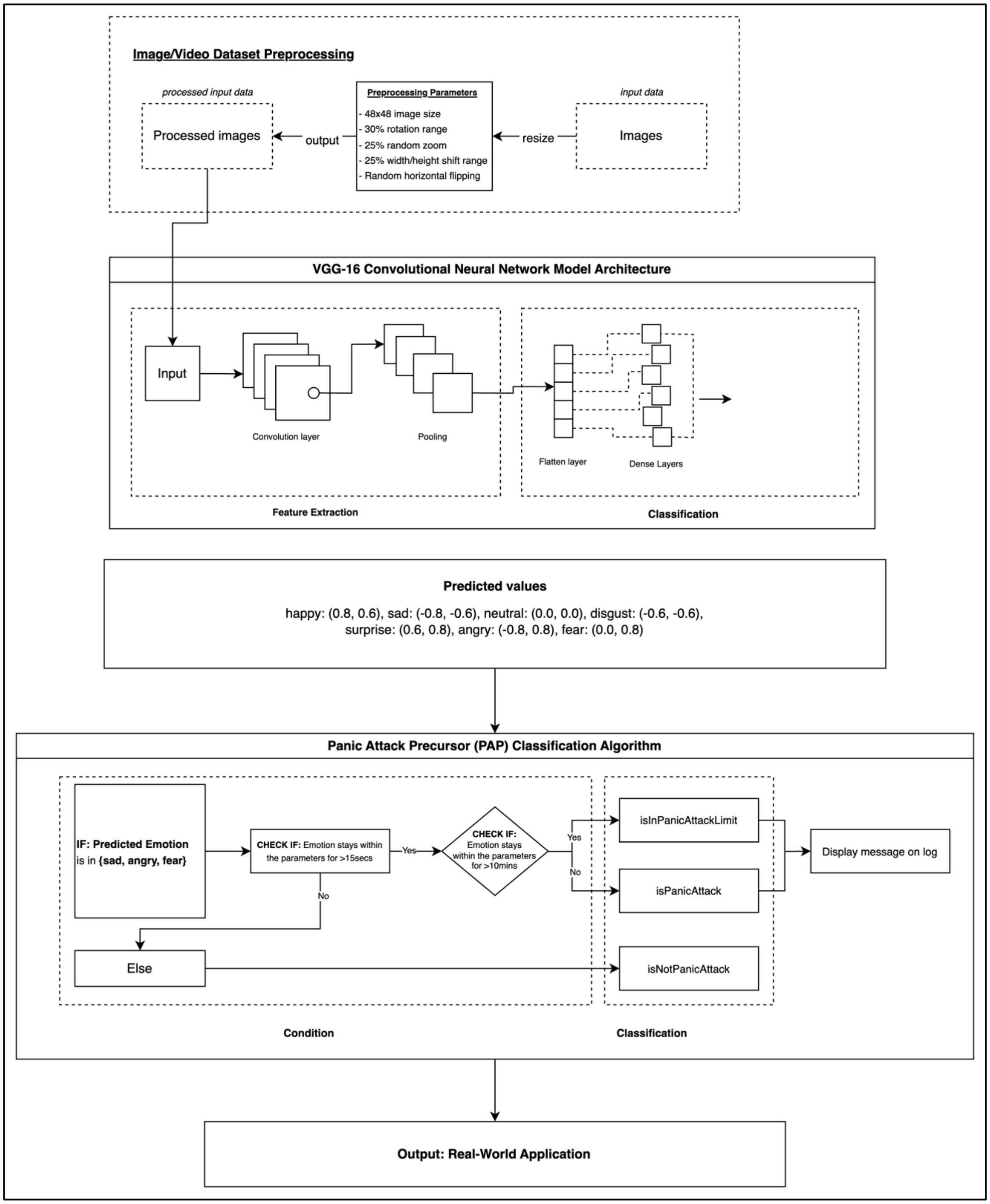


Fig. 4. Conceptual framework for the FER-CNN model.

Described in Figure 4 is the conceptual framework for the FER-CNN model developed in this study. The model accepted visual data, particularly video recordings of facial expressions of users, as input. Before the CNN model processed the data, it has undergone pre-processing where, for instance, the visual data was extracted from video frames, was resized, and was cropped into the desired dimension of 48x48. As detailed in Table 2, the model comprised a 48x48x3 input layer to represent the image. This involved a series of convolutional operations from the double convolutional layer with 64 feature maps. Each map utilized a 3x3 kernel and a stride level of 1. A ReLU layer is used as the activation layer. The output is down-sampled by a MaxPooling layer to 24x24x64 with a 2x2 kernel and ReLU activation function. This continued up until it reached the final convolutional layer block consisting of dimensions of a 3x3x512-sized convolutional layer and a MaxPooling layer of 1.5x1.5x3. The fully connected (FC) layers consist of two 512-unit dense layers with the ReLU as the activation function. The FC layers operated on a 1x1 feature map. The output layer is a dense layer with 2 units, designed for mapping the valence and arousal values in each captured facial expression. The mapped valence-arousal values were used to classify the panic attack emotions, as described in Figure 2. The binary classification results are displayed in a web application that was deployed in a web application.

3.6 Trustworthiness of the Study

To carefully establish the credibility and trustworthiness of the findings of the study, the researchers accurately and succinctly presented their methods for acquiring the necessary data needed in conducting the study while adhering to the ethical considerations set. This ensures that the outlined methods and the results are employed and obtained with the utmost commitment to scientific integrity.

4. Results and Discussions

4.1 Model Training Results

A total of 64,726 image data were used in training the FER-CNN model, wherein 70% of the dataset were distributed to the training set while the remaining 30% were distributed to the testing set. The augmentation parameters and the number of epochs varied per training iteration, an experiment on which parameters produce the best metrics for the model without overfitting. Figure 5 visualized the trend of the training process through a line graph.

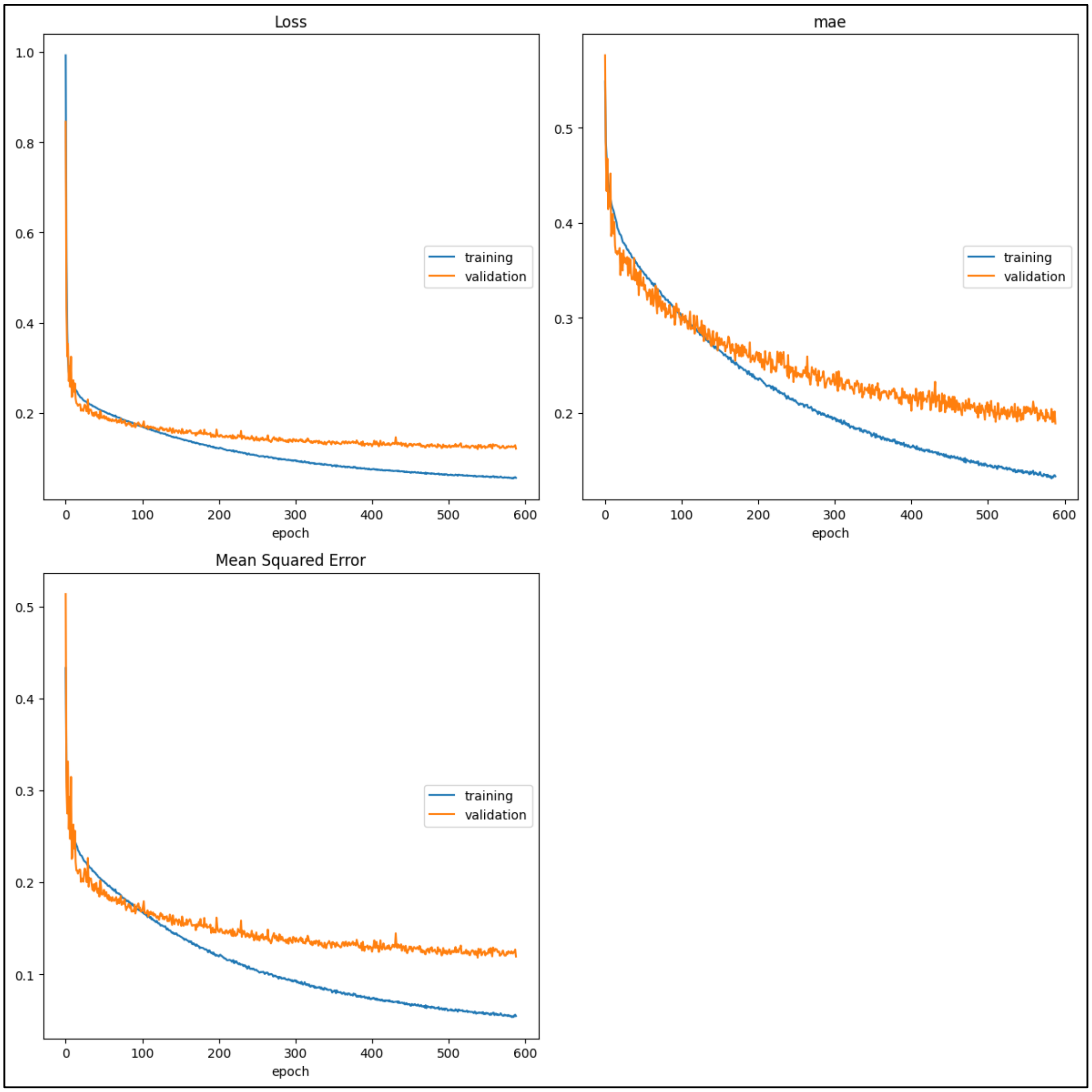


Fig. 5. Model training performance trend.

The testing set slowly plateaued at the 200th epoch but the training set continued learning. The model performance ceased to improve upon reaching the 539th epoch and with an early stopping value set at 50, the training stopped upon reaching the 589th epoch. The metrics used to evaluate the FER-CNN model are loss rate, Mean Absolute Error, Mean Square Error, R2 Score, and Explained Variance Score. The model training has undergone different processes from data cleaning and augmentation to modifying the model architecture. Upon its final iteration, the model has achieved the following results:

Table 4. Model training results

Iteration No.	Best Epoch	Set	Loss Rate	Mean Squared Error	Mean Absolute Error	R2 Score	Explained Variance Score
1	76	Train	0.4357	0.4312	-	-	-
		Test	0.4357	0.4312	-	-	-
2	80	Train	0.2282	0.2268	0.3801	33.17%	33.27%
		Test	0.2385	0.2370	0.4066		
3	64	Train	0.1839	0.1771	0.3272	45.78%	46.06%
		Test	0.2250	0.2177	0.4003		
4	125	Train	0.0840	0.0783	0.1994	56.99%	57.04%
		Test	0.1804	0.1745	0.3526		
5	208	Train	0.1091	0.1075	0.1432	61.15%	61.41%
		Test	0.1432	0.1416	0.2502		
6	**539**	**Train**	**0.0560**	**0.0543**	**0.1330**	**66.86%**	**66.94%**
(Final)		**Test**	**0.1207**	**0.1191**	**0.1887**		

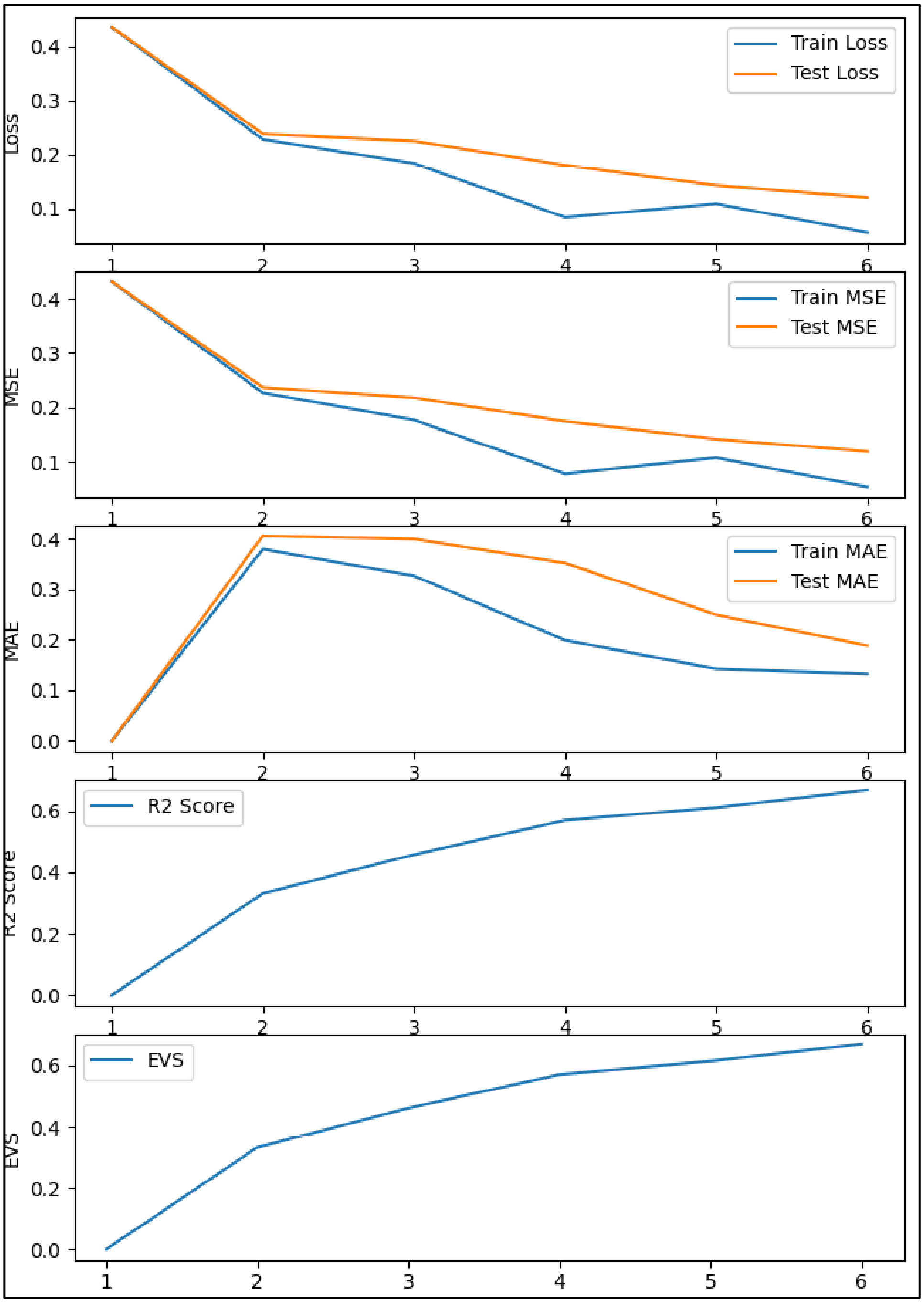


Fig. 6. Model training results visualization.

There is a 5% to 6% difference between the training set and the validation set due to the early stopping mechanism and the high number of training epochs. However, the differences are not a concerning indication of overfitting. As observed in Table 4, despite the larger gap, the model produced a much better output and a higher R-squared score. The final iteration has achieved an estimated Coefficient of Determination, also referred to as the R-squared (R2) Score, of 66.86%, the metrics used for measuring the performance of the FER-CNN model. Given that human behavior is simply difficult to predict or quantify, an R-squared score of at least 10% is acceptable. In the context of this paper, the R-squared score produced by the model is already highly satisfactory (Ozili, 2023).

The results were comparable to the performance of models using either the FER2013 dataset, VGG16 model architecture, or both. Table 5 provides a comparison of the performance of this FER-CNN model to similar models from other studies or literature.

Table 5. Comparative analysis of the datasets used in the FER-CNN model training.

Dataset	Set	Loss Rate	Mean Squared Error	Mean Absolute Error	R2 Score	Explained Variance Score
FER2013	Train	0.0687	0.1845	0.3481	57.42%	58.12%
	Test	0.0823	0.2013	0.3812		
AffectNet Lite	Train	0.1037	0.1078	0.1958	59.68%	60.03%
	Test	0.1181	0.1327	0.2497		
MMAFEDB	Train	0.0984	0.1687	0.2874	58.41%	58.84%
	Test	0.1487	0.1784	0.2954		
Combined (Used)	**Train**	**0.0560**	**0.0543**	**0.1330**	**66.86%**	**66.94%**
	Test	**0.1207**	**0.1191**	**0.1887**		

Table 6. Comparative analysis of FER-CNN-related models

Author	Dataset/Method	Overall Performance
Singh and Nasoz (2020)	FER2013 + 6-layer CNN	61.70%
Gan (2018)	FER2013 + VGGNet	60.98%
Manewa and Mayurathan (2020)	FER2013 + CNN	64.56%
Liu (2019)	FER2013 + Proposed Network	49.80%
	FER2013 + VGG16	37.40%
Rebea et al. (2024)	FER2013 + VGG16	66.13%
Zahara et al. (2020)	FER2013 + CNN	65.97%
Proposed FER-CNN Model	**FER2013 + VGG16**	**66.86%**

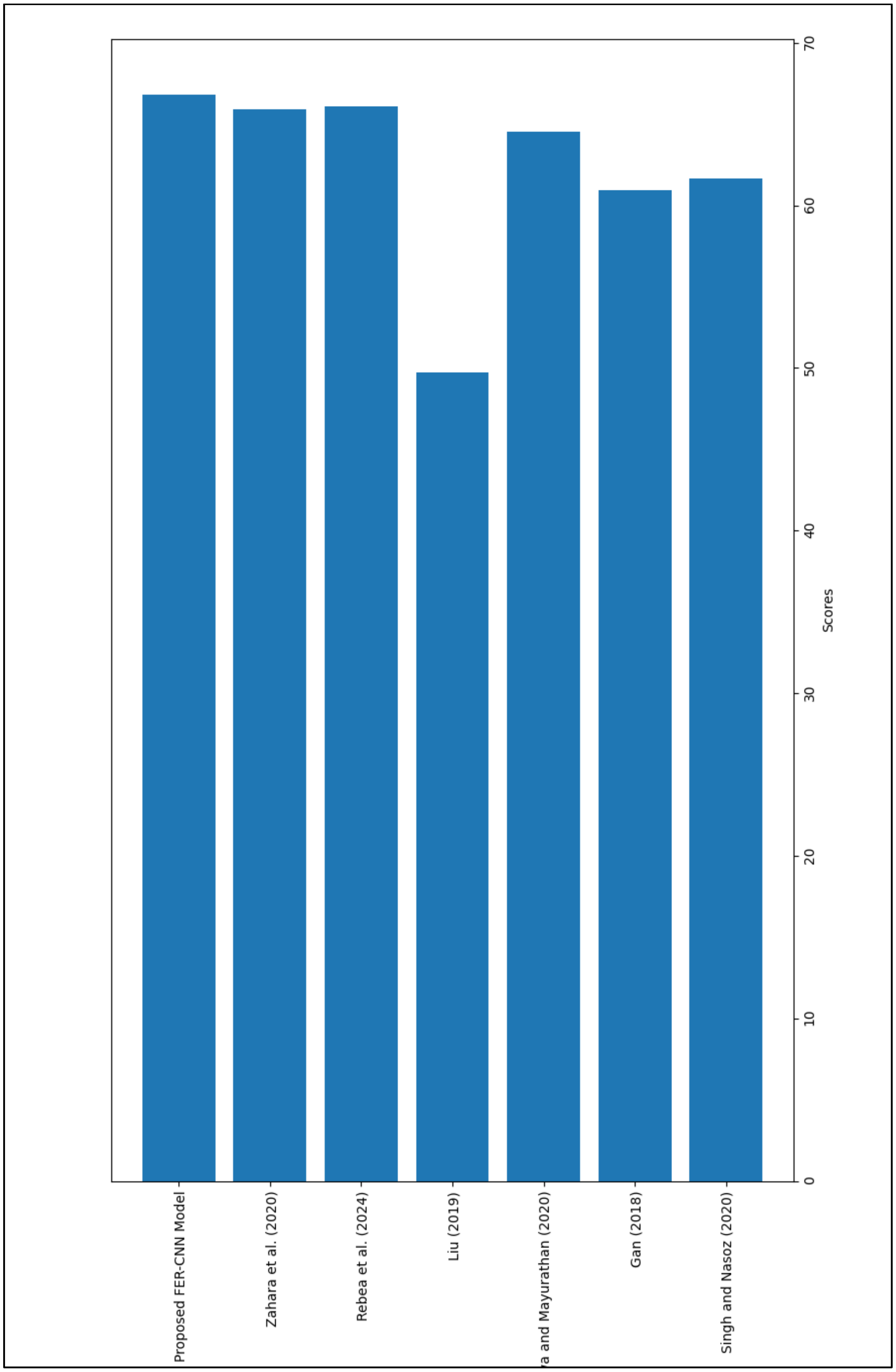


Fig. 7. Visualization of the Comparative analysis of the FER-CNN-related models

This outlined the limitations of the dataset used in this study and other literature and presented the strength of the methodologies employed in this model in comparison to other similar works. An in-depth discussion of the literature in Table 4 can be found in Chapter 2.3. To present the produced output, the model closely identified the valence and arousal values as illustrated in Figure 8:

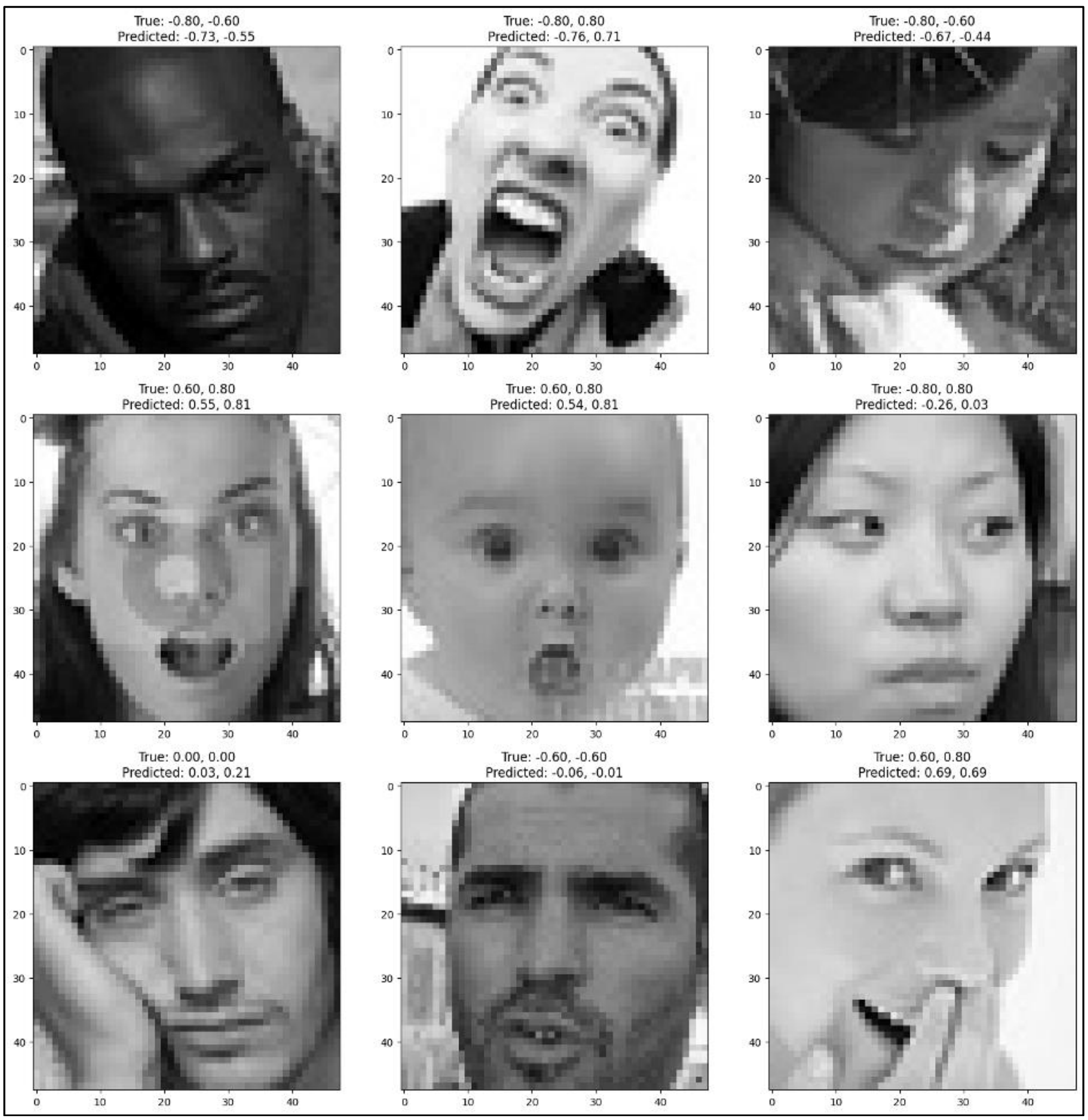


Fig. 8. Model performance in predicting Valence-Arousal values on images from the testing set.

The predicted continuous values allow the model to classify each image to its corresponding emotion without oversimplifying the complex emotional states, as opposed to the discrete classification method. As stated in Chapter 3.2, the continuous measures capture the intensity and nature of emotions, enabling the model to differentiate between subtle differences more accurately per emotional states.

4.2 Application Testing

The developed FER-CNN model was deployed in a web application running on a local server. The application is tested among the following devices, ranked from best performing to worst performing:

Table 7. Comparison of recommended hardware specifications

Device Type	Operating System	Specifications		Remarks
Laptop	macOS Sonoma 14.1.1	Processor	Apple M2 Pro	Recommended
		RAM	16GB	
		GPU	16-Core Apple M2 Pro	
Personal Computer	Windows 10	Processor	Ryzen 5 5600x	Recommended
		RAM	32GB 3200mhz	
		GPU	RTX 2070	
Laptop	Windows 11 Home	Processor	Ryzen 7 3750H	Recommended
		RAM	24GB	
		GPU	AMD Radeon Rx Vega 10 Graphics	
Laptop	Windows 11 Home	Processor	Intel i5-8250U	Minimum
		RAM	8GB	
		GPU	NVIDIA GeForce mx130	
Laptop	macOS Big Sur 11.0.1	Processor	2.7GHz 2-Core Intel Core i5	Minimum
		RAM	8GB	
		GPU	Intel Iris Graphics 6100	
Laptop	macOS Big Sur 11.0.1	Processor	1.4GHz 2-core Intel Core i5	Not recommended
		RAM	4GB	
		GPU	Intel HD Graphics 5000	

The recommended devices performed the detection through video upload smoothly with no lags and the live camera capture with minimal to no lags. Devices that meet the minimum requirements performed the detection through video upload with minimal to no lags and the live camera capture with obvious lags and mid to high frame rate drops. Lastly, devices with the lowest specifications and are not recommended for use produced obvious lags and high frame rate drops. Additionally, since the application is deployed in a website, it is also tested on the following browsers:

Table 8. Comparison of recommended browser specifications

Operating System	Browser	Version
macOS	Microsoft Edge	Version 121.0.2277.112 (arm64)
Windows	Microsoft Edge	Version 121.0.2277.128 (64-bit)
Windows	Google Chrome	Version 121.0.6167.185 (64-bit)

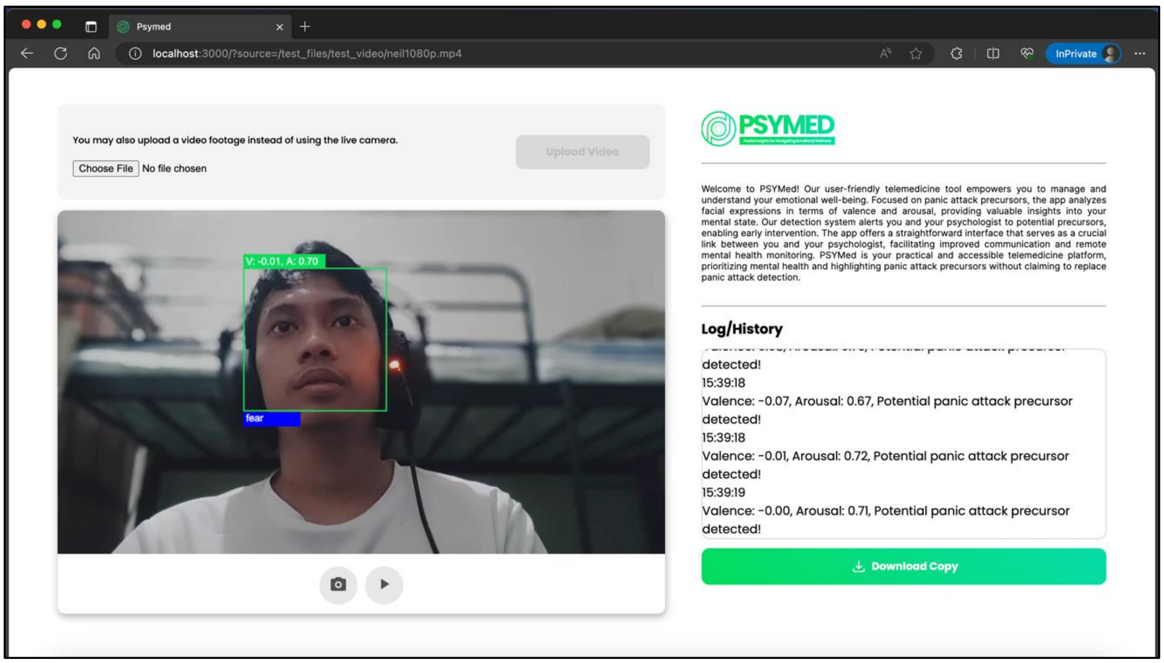


Fig. 9. Screenshot of the web application interface with logs detected by the PAPCA.

The application enabled users to use their camera for live capture and upload pre-recorded or existing footage for review. When a detection occurs, the event is logged on the history list, and when it is clicked, it opens a window with the captured image corresponding to when the precursor is detected. The application has additional features, such as a pause/play button that pauses both the video and detection, a screen capture button to save a screenshot of the currently playing video or live camera capture, and a download button for saving the log as a .csv file.

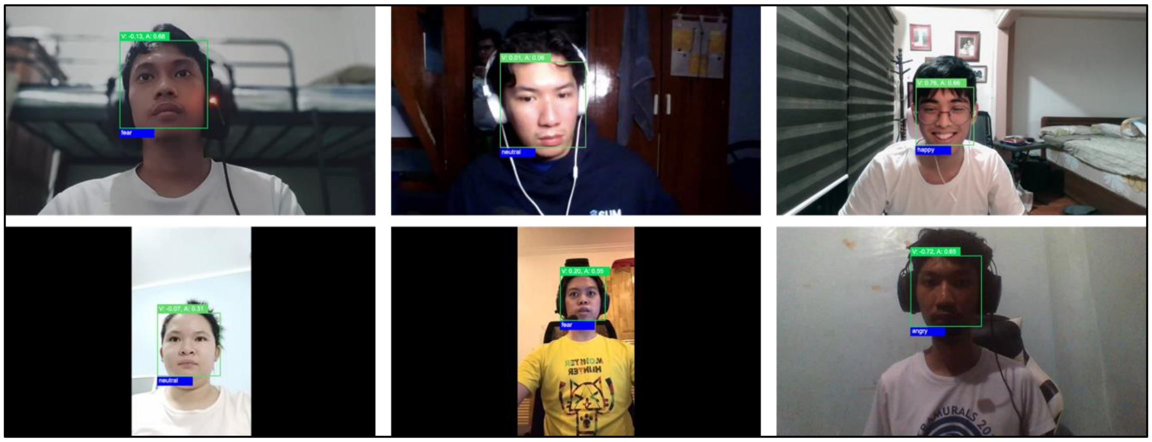


Fig. 10. Real-world testing output captured by the FER-CNN model.

The application is tested among 11 participants, gathered through purposive sampling. The requirements for the selection of these participants are the following: they must be 18 to 25 years old, must be knowledgeable in PC gaming for easier video game installation, and must have no pre-existing chronic and respiratory health conditions. Four (4) of the selected participants played *"Escape the Ayuwoki"* in single-player mode, while the remaining seven (7) played in a co-op horror game, *"Devour."* Table 6 presents the application testing analysis, describing the experiences of the participants while playing the game. The information about the experiences of the participants is gathered through a questionnaire released via Google Forms immediately after the game has concluded:

Table 9. Lived experiences of the participants

Codename	Player Mode	Has previously played games of a similar genre	Remarks
Lancer	Single-player	Yes	(Pre-game): • Has been anxious since knowing they will be playing a horror game. (In-game): • Highly immersed in the gameplay, causing fear and anxiety. • Easily frightened by the eerie game environment
Searchlight	Single-player	Yes	(Pre-game): • Has heard of the game before and is very anxious to try. • Heard about the game from friends. (In-game): • Highly immersed in the gameplay, causing fear and anxiety. • Easily frightened by the eerie game environment
Passkey	Single-player	No	(Pre-game): • Expressed anxiety towards playing horror games and is anxious while waiting at the game lobby or main menu.

			(In-game): • Laughed at the jump scares and thrilling moments of the game. • Was nervous but not enough to induce panic
Deacon	Single-player	No	(Pre-game): • Expressed anxiety towards playing horror games and is anxious while waiting at the game lobby or main menu. (In-game): • Only finished 1 level • Remained nervous throughout the game. • Experienced shock/surprise on jump scares. • Showed strong signs of panic attack precursors.
Rawhide	Multiplayer	No	(Pre-game): • Expressed anxiety towards playing horror games. (In-game): • Remained nervous throughout the game. • Experienced shock/surprise on jump scares

			• Easily frightened by the eerie game environment. • Showed strong signs of panic attack precursors.
Timberwolf	Multiplayer	Yes	(Pre-game): • Never played the game but are immune to playing horror games given their experience in horror gaming with friends. (In-game): • Showed no signs of panic attack precursors. • With their previous experience in playing similar games, playing with friends in a voice chat makes the game more humorous than scary. • Highly focused on the game objective
Eagle	Multiplayer	Yes	(Pre-game): • Have little experience in playing horror games but have played the game previously. • Nervous, overthinking, and predicting what will happen in-game. (In-game):

			• Showed little signs of panic attack precursors
Trailblazer	Multiplayer	No	(Pre-game): • Have little to no experience in playing horror games. • Afraid of ghosts, making them anxious (In-game): • Showed signs of panic attack precursors • Highly focused on winning the game but is overcome by the potential jump scares
Renegade	Multiplayer	Yes	(Pre-game): • Have little experience in playing horror games. (In-game): • Showed little to no signs of panic attack precursors. • Least anxious among all players, laughed at jump scares and thrilling moments of the game. • Fixated on the fact that the game was not real, making them less afraid
Mogul	Multiplayer	Yes	(Pre-game): • Had some experience in playing horror

			games but is anxious about playing them. (In-game): • Showed little signs of panic attack precursors but at some point, screamed and cried over a jump scare
Celtic	Multiplayer	Yes	(Pre-game): • Had some experience playing horror games and mentioned that horror games make them nervous more than movies of the same genre. (In-game): • Showed little signs of panic attack precursors but laughed it off very easily. • Feelings of anxiety come and go

The video footages acquired from the participants are used as video input for the application, which produced the results as described in Table 10:

Table 10. Real-world application testing analysis.

Codename	Camera Quality	Prominent Facial Feature/s	Log results	Remarks
Lancer	Bad	Wears glasses	No logged precursors	• Camera quality has a very low frame rate and is a little blurry, making it impossible to consistently capture the correct emotions.
Searchlight	Bad	N/A	No logged precursors	• Camera quality has a very low frame rate and is a little blurry, making it impossible to consistently capture the correct emotions. • The video is too short (at 03min and 50secs) to make a prediction
Passkey	Good	N/A	No logged precursors	• The video is too short (at 04min and 35secs) to make a prediction
Deacon	Good	Small Asian eyes	No logged precursors	• Started playing the game about 5mins later in recording, making the video too short to make a prediction
Rawhide	Good	N/A	True Positive	• Fast and strong panic attack precursor detection • Upon validating his lived experience in playing the game, detection started right on time
Timberwolf	Good	N/A	True Positive	• Well-lit footage, the camera captures the correct emotions. • Panic attack precursor prediction did not work since they did not feel any fear or

				anxiety while playing the game
Eagle	Good	N/A	True Positive	• Well-lit footage, the camera captures the correct emotions. • Upon validating his lived experience in playing the game, detection started right on time
Trailblazer	Bad	N/A	False Positive	• Low lighting affects the detection
Renegade	Good	Thick eyebrows, wearing glasses	False Positive	• Detection produces false positives due to thick eyebrows which are constantly being mistaken as anger, an emotion where eyebrows are very prominent
Mogul	Bad	N/A	No logged precursors	• Subject (face) placement is too low on the camera frame and • The subject is facing downward mid-game, making it difficult to capture
Celtic	Bad	Small Asian eyes	No logged precursors	• Detection remains at neutral due to bad lighting. • Light glaring is being captured above the subject and is reflected on the camera

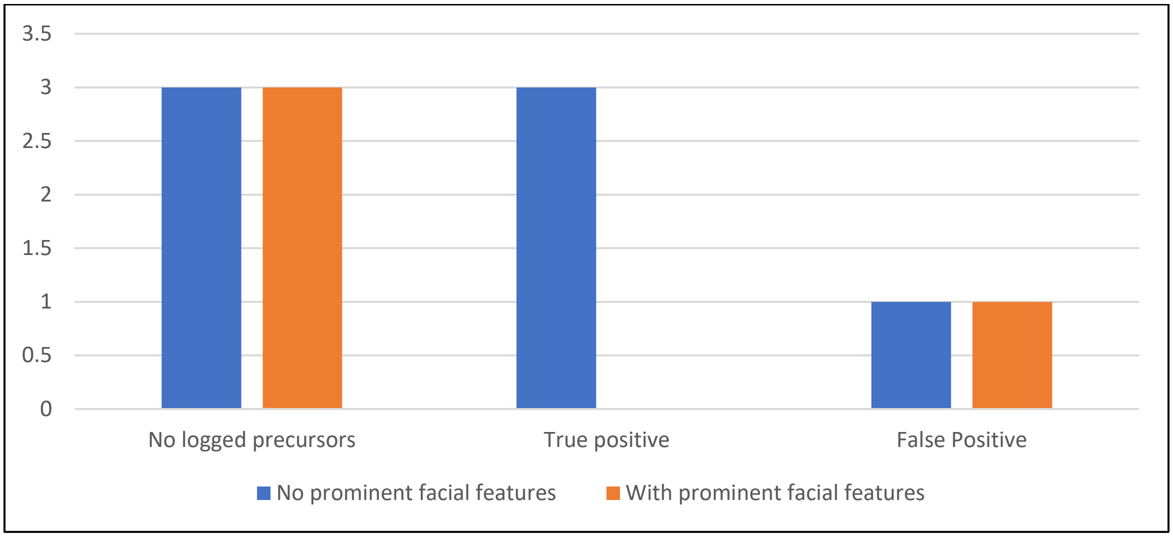


Fig. 11. Correlation of the prominent facial features to panic attack precursor detection.

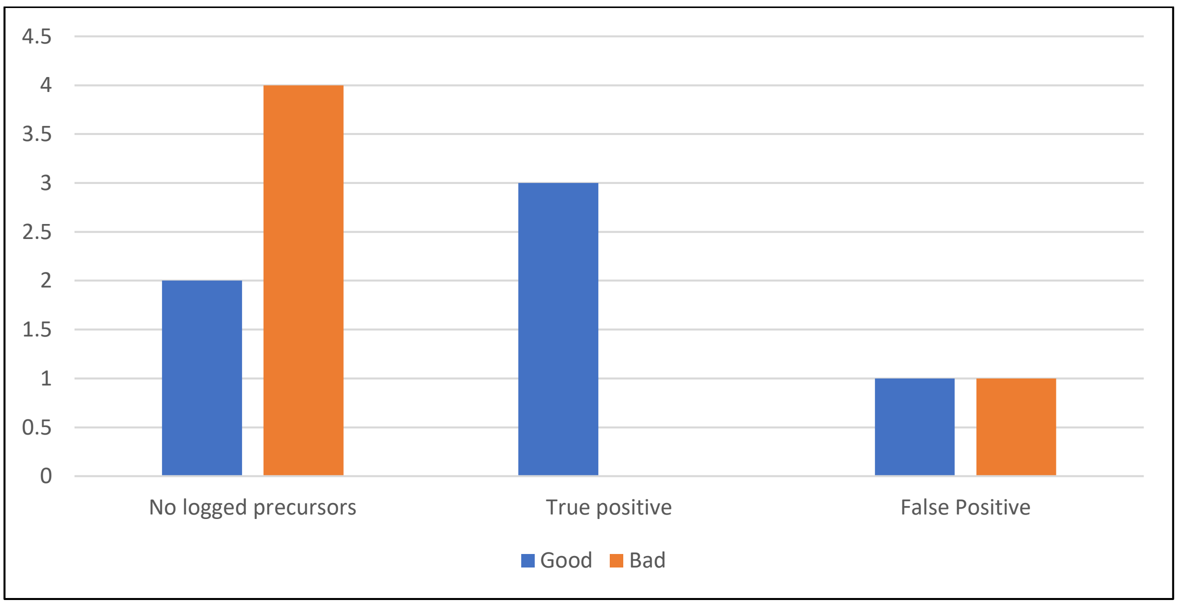
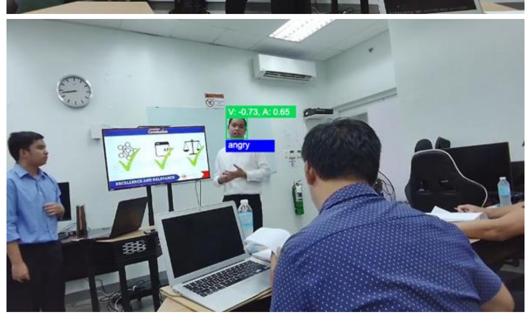


Fig. 12. Correlation of camera quality to panic attack precursor detection.

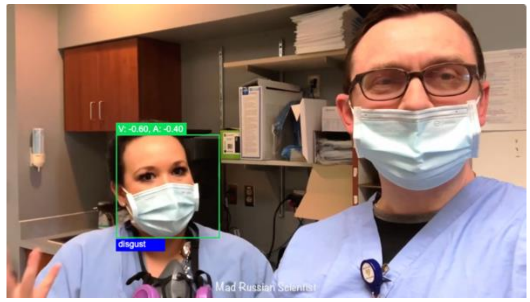
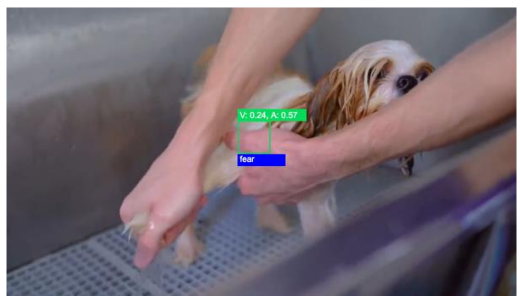
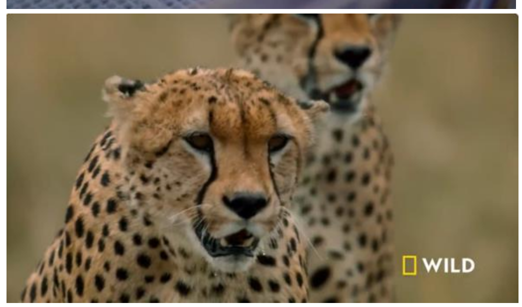
As described in the table above, the application has rendered mixed results due to the limitations of the application. The FER-CNN model is highly sensitive, making accurate emotion detection on test subjects with prominent facial features such as small eyes and thick eyebrows, test subjects within a poorly lit environment, and a camera device that produces a low frame rate more difficult. For instance, when detecting emotions in participant *"Renegade,"* the model misidentifies the emotion as "angry" where the eyebrow shape and thickness are very significant. The model also found it very difficult to identify emotions in test subjects with small eyes as eyes are very important in determining emotions through facial expressions. Without these limitations, such as those with participants *"Rawhide," "Timberwolf," and "Eagle,"* the model can accurately predict panic attack precursors, even matching the lived experiences described by the participants themselves.

In addition to the previous testing method, the model was also tested among a distant multi-face setup, such as in a live presentation, animal faces, a person wearing a surgical mask, and animated characters. Video footages for the multi-face setup were captured during an onsite live presentation, while other test subjects make use of footage from YouTube. The results are described in Table 11.

Table 11. Supplementary real-world application testing analysis

Test Setup	Test Subject	Sample detection (image)	Log results/Remarks
Multi-face Setup (1.5m distance), frontal view	Human, group		**True Positive,** the facial detection model is unable to detect multiple faces and can only scan one face at a time. The distance of the subject from the camera makes it difficult for the model to recognize the other faces. Thus,

			it can detect some faces and log predictions in a few instances.
Multi-face Setup (1m distance), frontal view	Human, group		**No logged precursors,** the facial detection model is unable to detect multiple faces and can only scan one face at a time, shifting from one face to another in every millisecond.
Multi-face Setup (1m distance), side profile view	Human, group		**True Positive,** the facial detection model is unable to detect multiple faces and can only scan one face at a time. The distance of the subject from the camera makes it difficult for the model to recognize the other faces. Thus, it can detect some faces and log predictions in a few instances. However, the model is inconsistently detecting faces in full-side view.

Single face, face mask-covered	Human		**No logged precursors,** the facial detection model can detect faces among subjects wearing a face mask but is only generalizing on the emotion detection. Thus, it is difficult to conclude a panic attack precursor.
Animal face	Shih Tzu puppy		**False positive,** facial detection model is falsely detecting on non-face subjects.
Animal face	Cheetah		**No detection,** The facial detection model does not detect on non-human face subjects.
Computer-generated animation	Animated human		**No logged precursors,** the facial detection model can detect faces among 3D-animated human subjects. The used footage is too short to conclude a panic attack precursor

Computer-generated animation	Animated animal	 	**No logged precursors,** the facial detection model can detect faces with an extreme display of emotions, whether human or not. However, in most instances, it is unable to detect faces that do not show a hint of resemblance to a human face.
Traditional/ Hand-drawn animation	Animated human		**No logged precursors,** the facial detection model can detect faces among 2D-animated human subjects. The used footage is too short to conclude a panic attack precursor.

5. Conclusion and Recommendation

5.1 Conclusion

This paper discussed the development of the FER-CNN model for detecting the precursors of a panic attack. The study has successfully achieved the objectives defined in the statement of the problem.

The first objective pertains to the consolidation of the FER2013 dataset with other facial image datasets such as MMAFEDB and a lighter version of the FER-AffectNet dataset. The model was evaluated according to its loss rate, Mean Squared Error, Mean Absolute Error, and R-squared score. The datasets were used as the training data for the model training wherein, in several training iterations, has achieved a loss rate of 5.60%, Mean Squared Error of 5.43%, and Mean Absolute Error of 13.30% on the training set, and a loss rate of 12.07%, Mean Squared Error of 11.91%, and Mean Absolute Error of 18.87%. There is a 5% to 6% difference between the training set and the validation set due to the early stopping mechanism and the high number of training epochs. The differences were not a concerning indication of overfitting. With these model training results, the model has achieved a Coefficient of Determination or R-squared score of 66.86%, achieving the second objective.

The model was then deployed to an application, PSYMed, where it was used along with a panic attack detection algorithm for classifying panic attack patterns in real-world inputs. The model excelled in detecting panic attack precursors through facial expressions in real-world scenarios, especially under optimal conditions such as a well-lit environment and clear, high frame-rate cameras. The model also demonstrated a higher accuracy in detecting subjects exhibiting generic facial features and minimal obstructions such as eyewear, and in detecting single-face subjects compared to multi-face subjects due to computational limitations. If these conditions are met, the FER-CNN and panic attack precursor detection yield superior and more accurate results, achieving the third objective of the study.

Given the results presented in Chapter 4, it is concluded that the paper was able to achieve the objectives stated in the problem statement in Chapter 1. The study represented a pioneering study and is one of the earliest forms of applications of machine learning in psychology especially in the realm of facial expression recognition. This establishes the groundwork for future research efforts in this emerging field.

5.2 Recommendation

The novelty of this paper positions it as a foundation for future studies that seek to forecast panic attacks and similar conditions through facial expressions, laying the groundwork for future research efforts in this emerging field. Here are several recommendations to consider for the improvement of this study:

Given that the model relies on valence and arousal values for classifying emotions through facial expressions, consider training it in a more suitable dataset, such as the AffectNet dataset. To further validate its intended application, the researchers also recommend conducting a clinical trial under controlled conditions supervised by trained medical professionals to ensure more precise results. The camera quality highly affects the detection system, so it is highly recommended to use a web camera that produces a high frame rate to ensure that the video is smoothly captured. It is also recommended that the subjects are in a well-lit environment for the camera to capture better. By addressing the limitations, the performance of the model can be further improved, resulting in more reliable outputs.

The application's utility extends beyond telemedicine counseling as it can also be deployed in different scenarios where panic attacks can occur. For instance, the application can be used in a hybrid classroom to identify potential panic attacks among students, or in office environments to monitor employees' well-being and detect signs of distress. Through further refinement and application, this research holds a promising future for intersecting technology and mental health care.

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Appendices

Appendix A: Letter to Healthcare Professional in Sto. Tomas Davao del Norte

MAPÚA MALAYAN COLLEGES MINDANAO

To whom it may concern,

I hope this letter finds you in good health and high spirits. I am John Joshua Mesia, a 4th year Computer Science student from Mapúa Malayan Colleges Mindanao. I am sending this letter on behalf of my group to request your expertise and professional opinion in the matter of determining the mental healthcare in the municipality and the importance of having these facilities and practitioners in the area.

In pursuit of academic excellence and community development, we are currently conducting a study titled "**Detecting Panic Attack Precursors using a Convolutional Neural Network-based Facial Expression Recognition Model**." In this study initiative we aim to develop an image-recognition model to detect precursors of a panic attack through facial expressions.

We believe that this study will help mental healthcare professionals in providing mental health consultations among members of underserved communities such as Brgy. Tibal-og, Sto. Tomas, Davao del Norte. With that, we would like to request your participation in an **interview** that will help our study gather important information based on your professional opinion.

We greatly appreciate your consideration of our request and look forward to the opportunity to collaborate with you on this important endeavor. Your participation will undoubtedly make a meaningful difference in our efforts.

Thank you for your time and consideration.

Sincerely,

John Joshua C. Mesia

Researcher

Appendix B: Letter to Dataset Validators

Dear _______________,

I hope this letter finds you well. We are **4th year BS Computer Science students** from the College of Computer and Information Science of **Mapúa Malayan Colleges Mindanao**, and we are writing to formally extend an invitation for you to serve as one of our data validators for our thesis project. Considering your membership to the Psychological Association of the Philippines, we believe that your expertise and guidance would greatly contribute to the successful completion of our research.

Our thesis, entitled **"PSYMed: Detecting Panic Attack Precursors using a Convolutional Neural Network-based Behavioral Pattern Recognition Model,"** aims to develop a machine learning model, deployed in a telemedicine software, that can detect potential panic attacks among patients through their facial expression during an online consultation with their psychologist.

As part of our objectives, we are to collect images of panic attack facial expressions from the Internet to craft the dataset that we will be using for our study. With this, we are looking for a group of psychologists to validate our dataset, ensuring its accuracy and usability for this project.

Upon signing this letter, you confirm your involvement and commitment to contributing your expertise to our study. Rest assured that your communication preferences will always be on top of our concern, and we ensure to only seek for consultation on your most convenient and available schedule.

We greatly appreciate your consideration of our request and look forward to the opportunity to work together on this exciting project.

Thank you for your time and consideration.

Best regards,

Ria Millicent A. Cordero   Angelie Badar   John Joshua C. Mesia

Engr. Neil P. Magloyuan, MEE, PCpE

Thesis Adviser

Appendix C: Confirmation of Dataset Validity

CONFIRMATION OF DATASET VALIDITY

Important information:

(1) This form is created by the 23-CS-002 group for their thesis title, *"PSYMed: Detecting Panic Attack Precursors using a Convolutional Neural Network-based Facial Expression Recognition Model."* The form cannot be used and reproduced by persons outside the group.
(2) This form serves as a proof of document for the data validation process of hired/appointed validators.
(3) You may submit this document physically, in PDF, or in scanned format.

COURSE CODE	CS200D-1	GROUP CODE	CS-002

NAME OF STUDENTS (SURNAME, GIVEN NAME, MI.)	STUDENT NO.	MOBILE NUMBER	E-MAIL
CORDERO, RIA MILLICENT A.	2018100403	09496979279	rmCordero@mcm.edu.ph
MESIA, John Joshua C.	2018103209	09618336269	jjMesia@mcm.edu.ph
BADAR, Angelie	2018104420	09924728077	aBadar@mcm.edu.ph

Upon signing this document, the validator confirms that the dataset is valid and can be used to conduct the study:

☐ **Agree** ☐ **Disagree**

If disagree, why? Write "N/A" if none or if the question does not apply.

Do you have any comments and suggestions?

Validator's information:

(1) The collected information will be used for contact purposes only.

Name (Surname, Given Name, M.I.)	Position	Contact Number	Email address

SIGNED BY: NOTED BY:

Data Validator
(Signature over printed name and date)

Thesis Adviser
(Signature over printed name and date)

Appendix D: Letter to Consultant

Dear _____________,

I hope this letter finds you well. We are **4th year BS Computer Science students** from the College of Computer and Information Science of **Mapúa Malayan Colleges Mindanao**, and we are writing to formally extend an invitation for you to serve as one of our Consultant for our thesis project. Considering your membership to the Psychological Association of the Philippines, we believe that your expertise and guidance would greatly contribute to the successful completion of our research.

Our thesis, entitled **"PSYMed: Detecting Panic Attack Precursors using Convolutional Neural Network-based Behavioral Pattern Recognition Model,"** aims to develop a machine learning model, that can detect potential panic attacks among patients through their facial expression during an online consultation with their psychologist.

Upon signing this letter, you confirm your involvement and commitment to contributing your expertise to our study. Rest assured that your communication preferences will always be on top of our concern, and we assure you to only seek consultation on your most convenient and available schedule.

We greatly appreciate your consideration of our request and look forward to the opportunity to work together on this exciting project.

Thank you for your time and consideration.

Best regards,

Ria Millicent A. Cordero　　Angelie Badar　　John Joshua C. Mesia

Noted by:

Engr. Neil P. Magloyuan, MEE, PCpE
Thesis Adviser

Appendix E: Search for Participants Form

PSYMed: Detecting Panic Attack Precursors using Convolutional Neural Network-based Behavioral Pattern Recognition Model

Good day, we are 4th year BS Computer Science students from the College of Computer and Information Science of Mapúa Malayan Colleges Mindanao. We are currently seeking participants for our thesis "PSYMed: Detecting Panic Attack Precursors using Convolutional Neural Network-based Behavioral Pattern Recognition Model". Our thesis aims to develop a machine learning model deployed in telemedicine software that can detect potential panic attack precursors among patients through their facial expressions during an online consultation with their psychologist.

In line with this, by answering this form, your identity will remain confidential and will only be used for our thesis. Your privacy is of the utmost importance, and we will diligently safeguard any personal information provided.

Full Name *
(Surname, Given Name, Middle Name)

Your answer

Do you currently have any pre-existing health conditions or illnesses? Please select all that apply. *

- [ ] None
- [ ] Chronic conditions (e.g., hypertension, diabetes)
- [ ] Respiratory conditions (e.g., asthma, allergies)
- [ ] Mental health conditions
- [ ] Other:

Please indicate your general availability for participation. Select all that apply: *

- [ ] Weekdays mornings
- [ ] Weekdays afternoons
- [ ] Weekdays evenings
- [ ] Weekends mornings
- [ ] Weekends afternoons
- [ ] Weekends evenings
- [ ] Other:

Would you be willing to participate in our thesis study as a research participant? *

- ( ) Yes
- ( ) No

Appendix F: Participants experience form

PSYMed: Detecting Panic Attack Precursors using Convolutional Neural Network-based Behavioral Pattern Recognition Model

This survey is to know your experiences during and after the testing phase. Your answers will be kept confidential. Thank you!

What is your name? *

Your answer

What game did you play? *

- ◯ Escape the Ayuwoki
- ◯ Devour

Have you played horror games before? *

- ◯ Yes
- ◯ No

Are you afraid when playing the game? *

- ◯ Yes
- ◯ No

Why or Why not? *

Your answer

If you experienced panic attack while playing the game, how long do you think it manifest before it stop? *

Your answer

Share your overall experience (before, during and after the game) *

Your answer