MAPÚA MALAYAN COLLEGES MINDANAO

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

Commented [RC1]: Revise title

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

Bachelor of Science in Computer Science

Thesis Adviser
Neil P. Magloyuan, MEE PCpE
College of Computer and Information Science

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

by

Ria Millicent A. Cordero

John Joshua C. Mesia

Angelie Badar

A Research Submitted to the College of Computer and Information Science
in Partial Fulfillment of the Requirements for Thesis 1

Bachelor of Science in Computer Science

Mapúa Malayan Colleges Mindanao
Davao City

August 2023

TABLE OF CONTENTS

TITLE PAGE	i
TABLE OF CONTENTS	ii
LIST OF TABLES	iii
LIST OF FIGURES	iv
LIST OF ABBREVIATIONS	v
ARTICLE 1: PSYMED: DETECTING PANIC ATTACK PRECURSORS USING A CONVOLUTIONAL NEURAL NETWORK-BASED FACIAL EXPRESSION RECOGNITION MODEL	1
REFERENCES	26

LIST OF TABLES

ARTICLE 1

Table 1: .

Table 2: .

Table 3: .

Table 4: .

Table 5: .

Table 6: .

LIST OF FIGURES

ARTICLE 1

Figure 1: FER2013 dataset training framework 22

Figure 2: Valence-Arousal Circumplex 23

Figure 3: FER-CNN Model for classifying binary output 25

Figure 4: FER-CNN Model applied for real-world testing framework 27

Figure 5: Low-fidelity wireframe and interface design for the telemedicine application 27

Figure 6: Concept framework for the FER-CNN model 28

LIST OF ABBREVIATIONS

FER-CNN	Facial Expression Recognition-Convolutional Neural Network
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, 5th Edition
FER	Facial Expression Recognition
CNN	Convolutional Neural Network

Article 1

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

Ria Millicent A. Cordero[a]*, Angelie Badar[a], John Joshua C. Mesia[a]

[a]College of Computer and Information and Science, Mapúa Malayan Colleges Mindanao, Davao City, Philippines 8000

Emails: rmCordero@mcm.edu.ph, aBadar@mcm.edu.ph, jjMesia@mcm.edu.ph

*Ria Millicent A. Cordero

College of Computer and Information Science

Mapúa Malayan Colleges Mindanao

Gen. Douglas MacArthur Hwy, Talomo

Davao City, Philippines

Email rmCordero@mcm.edu.

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 do not immediately imply the presence of a mental health disorder, such as major depressive disorder (MDD), anxiety disorders, 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 the 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, where 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 for 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 attitude 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 to be 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 most especially among patients with chronic conditions (Mehrotra et al., 2020). In the context of mental healthcare, considering that inaccessibility is a huge factor towards 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 model that can recognize behavioral patterns manifesting through facial expressions and classify them as panic attacks.

Convolutional Neural Networks (CNN) are deep learning algorithms within the Artificial Neural Network (ANN) class commonly used for analyzing and processing input data, usually for image classification. CNNs commonly 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:

Commented [RC2]: Add dataset creation

1. Create a dataset containing the facial expressions of a panic attack.
2. Develop a telemedicine application in which the FER-CNN is integrated to.
3. Evaluate the effectiveness of Convolutional Neural Networks in recognizing and classifying facial expression patterns associated with panic attacks.
4. Test the effectiveness of the FER-CNN-applied telemedicine software in detecting panic attack precursors.

The proposed study is targeted towards underserved areas in 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 have 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-experimental research among the residents of the municipality aged 18 to 25 years old.

Commented [RC3]: Elaborate on why we intend to conduct the study on Sto. Tomas

Commented [JM4R3]: check please

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 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 related literatures, 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

Up 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, agitated 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 do not immediately assume that a person has a mental health disorder, such as major depressive disorder (MDD), anxiety disorders, 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 literatures that thoroughly describes the experience of having a panic attack among adults, there is not much literature pertaining to panic attack among adolescents. Thus, Hewitt 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 in 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 for 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 have 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 with the healthy subjects. The computer simulation exposure posed a 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.

2.2. Convolutional Neural Networks in Healthcare

Convolutional Neural Networks (CNN) are a deep learning algorithm within the Artificial Neural Network (ANN) class that is highly used in image classification and recognition, semantic segmentation, and machine translation (Xin et al., 2020). CNNs utilize three architectural ideas— local receptive fields, shared weights, weight replication, and spatial or temporal subsampling— to achieve a certain degree of shift and distortion invariance (LeCun & Bengio, 1995). The utilization of CNNs addresses critical challenges in medical data analysis, since healthcare datasets often involve complex and intricate visual information such as medical images and scans. This means that CNN can accurately identify crucial markers like tumors, fractures and even emotional state being of the patient. This means that a technology supported with a CNN enhances healthcare practices and significantly contributes to patient care.

As a commonly used neural network model in image recognition, CNNs, along with other algorithms, can also be used for classifying skin diseases. The Deep Convolutional Neural Network and Error Correcting Output Codes (ECOC) Support Vector Machine (SVM) are the proposed scheme for classifying skin lesion images into five categories: healthy, eczema, benign, acne, or malignant melanoma. The images in the dataset were divided into training and testing datasets with a ratio of 70:30, where 70% is for the training, and 30% is for testing. A pre-trained CNN model called AlexNET was used to extract the feature, and an ECOC SVM classifier was used for the classification. The classification using ECOC SVM classifier achieved an overall accuracy of 86.21% (Hameed et al., 2018).

In classifying microscopic bacteria images from microscopic samples, deep Convolutional network with a support vector machine (SVM), preparing the dataset used in this study consists of two steps: the assortment of microscopic bacteria images and pre-processing. Seven bacteria species that can cause disease (pathogenicity) to human health were chosen in the images. The automatic feature extraction was done using the Inception-V3 DCNN model, and the SVM classifier with RBF kernels was used for the classification. The proposed model has a classification accuracy of 96.07% in the test data, which successfully classified seven types of bacteria samples (Ahmed et al., 2019).

Transfer Learning of Deep Convolutional Neural Network (DCNN) and Support Vector Machine (SVM) was utilized in automating the mass classification in the breast. Classifying the mass of the breast is a difficult task to achieve due to its large variations in boundary, size, shape, and texture. The INbreast dataset used in this study was acquired at a breast center in Portugal. The DCNN is used for feature extraction and SVM in classifying the mass and non-mass tissue. Based on the result, the pre-trained DCNN can extract distinctive high-level features, and the SVM classifier can successfully distinguish the presence of mass and non-mass in the breast (Hasan et al., 2020).

Early detection of heart disease and diagnosis was proposed in the study of Pan et al. (2020) by utilizing an Enhanced Deep learning-assisted Convolutional Neural Network (EDCNN). The EDCNN model primarily focused on a deeper architecture, encompassing a multilayer perceptron model with regularization learning techniques. Aligned with this, datasets from the UCI repository were employed for diagnostic purposes, and in classifying fundamental ECG heartbeats, feature extraction was conducted using both CNN classifier and multi-layer perceptron (MLP). The EDCNN system has been deployed on the Internet of Medical Things Platform (IoMT) to serve as a decision support system. This aids physicians in efficiently diagnosing heart patient data within the cloud platform. The experimental outcomes indicate that a versatile configuration with fine-tuned hyperparameters can achieve an accuracy rate as high as 99.1%.

Rai et al. (2018) proposed Darwin, an intelligent healthcare assistant chatbot that enables users to check for symptoms of common diseases, suggest medical consultation when needed, and recommend and monitor exercise or workout routines together with a comprehensive exercise guide. Users can make use of the Darwin chatbot through the Facebook Messenger application. Furthermore, this healthcare assistant utilized a Convolutional Neural Network (CNN) built using TensorFlow library for message intent identification to classify the message from the users. The dataset used to train this chatbot was gathered from different online sources through web scraping. The results show that the proponents achieved an accuracy rate of 97.37% in the trained model and 98.39% in the testing phase.

2.3. 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 using CNN and SoftMax function on Captured Images (Deopa et al., 2019), Facial Emotion Recognition Using a Deep Convolutional Neural

Network by (Pranav et al., 2020), and Audio-visual emotion recognition using a hybrid deep convolutional neural network based on census transform by (Cornejo & Pedrini, 2019). These studies incorporated CNNs in analyzing facial emotion patterns.

Convolutional Neural Networks 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).

A Hybrid Deep CNN was developed for audio-visual emotion recognition. Facial expressions were extracted from videos using a visual network based on Census-Transform. In the video fusion, max pooling was applied. The separate process for analyzing audio features is described in Chapter 2.3. The two features were fused, resulting in a global feature with 104448 dimensions, which required employing multiple reduction techniques such as Principal Component Analysis and Linear Discriminant Analysis (PCA-LDA). The accuracy of the audio-visual classification was compared using traditional classification algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors, Logistic Regression, and Gaussian-Naïve Bayes (Cornejo & Pedrini, 2019).

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 convolutional neural networks (CNN), 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 Convolutional Neural Network (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 micro expression systems encompasses two main stages: 1) Training Process and 2) 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 Convolutional Neural Network (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 Facial Expression Recognition: 1) Automated process for feature extraction by utilizing a convolutional neural network 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 facial expression recognition, there are two convolutional layers (the first layer uses six masks, and the second layer uses 12 masks) and two subsampling layers. It’s 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 Convolutional Neural Network (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%.

2.4. Modern Technologies in Psychological Consultations

In recent years, the use of modern technology in a 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 has significantly increased during the COVID-19 pandemic. A study by Record et al. (2021) a telemedicine can similarly mimic a traditional health visit by a patient to the clinics 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 which patients and clinicians have high satisfaction because of the quality of communication and patient-centeredness and convenience factor 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 the 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 in 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 patients 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, the Great Britain, and India. CATs make assistance in psychological consultations a lot easier for mental health workers and expanding treatments among underserved areas a lot more efficient. 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 of providing support among students seeking for 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 for 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 for psychological help being opened for greater research and exploration.

Telemedicine is also being practiced in the national setting and was made popular during the 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 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 became 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, 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. In a study by Matsumoto et al. (2018) assesses the feasibility of video conferencing as a medium for providing CBT among remote patients with OCD, PD, and SAD. In this study, 30 patients received 16 sessions of video conference delivered ICBT individually, conducted by a single therapist. 86% of these participants have stated their satisfaction towards 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. As a 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 CBT technologies 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 deems 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 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 effectivity 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 to in-person medical service, telemedicine in the field of psychiatry is a validated and effective medical practice that increases the 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 to high-quality nursing practices. Telemedicine has been proven to be an effective supporting tool to mental healthcare services, but its ability to fully substitute in-person medical consultations is yet to be determined.

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 Convolutional Neural Networks (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 uses an applied-experimental research design that combines both applied and experimental research to address the problems stated in Chapter 1. Applied research design mainly focuses on developing the solution, in this case, the CNN model, to be applied in real-world settings, whereas experimental design focuses on the real-world experimental treatment where the CNN model will be applied in the experimental treatment group. As an evaluation, the results will be compared to the control group, which will use the traditional methods of diagnosing panic attacks, such as manually identifying panic attack patterns described in the DSM-5 (American Psychiatric Association, 2013). Through this design, the researchers will determine whether the developed CNN model improves the diagnosis of panic attacks by recognizing its facial cues when applied in a telemedicine setup.

3.2 Data Collection

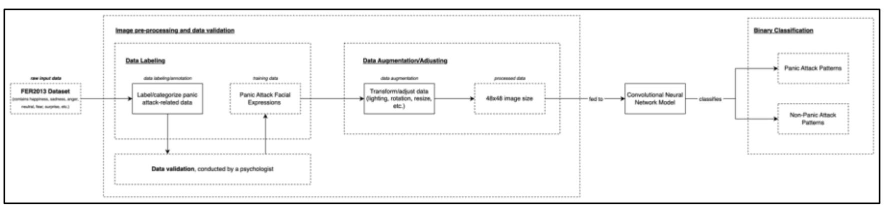

Figure 1: FER2013 dataset training framework

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 shall make use of the Facial Expression Recognition 2013 (FER2013) dataset, which consists of images labelled with one of seven emotions: (1) anger, (2) disgust, (3) fear, (4) happiness, (5) sadness, (6) surprise, or (7) neutral. Since the dataset does not contain images labelled as "panic attack" specifically, the dataset must undergo a data labelling process where relevant images, such as those that show distress or intense emotions, would be selected from the dataset. In addition to this, video frames of facial expressions amidst panic attack taken from video streaming websites like YouTube will be used as a secondary data source.

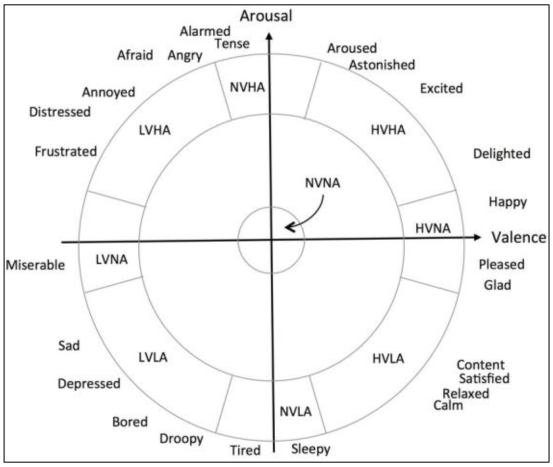

Figure 2: Valence-Arousal Circumplex (Lang et al., 1995)

The emotions from the FER2013 dataset will be grouped according to the Valence-Arousal Circumplex 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). In this study, the circumplex shall serve as the primary annotation criterion for identifying the panic-attack related facial expressions, in which must belong to the neutral-valence-high arousal (NVHA), low-valence-high-arousal (LVHA), and low-valence-neutral-arousal (LVNA). This shall be validated by the study's partner psychologists. The annotated dataset shall be balanced with the FER2013 dataset to ensure a diverse range of emotions and prevent biases.

3.3 Instrument

This study will make use of 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 an extensive documentation and an actively supportive community that can provide resources and support for the development phase of the CNN model.

3.4. Data Analysis Plan

Data Pre-processing: A data annotation shall be conducted to select images that show distress or intense emotions and can be identified as a panic attack. The images will be selected from the FER2013 dataset and video frames captured from YouTube. The data labeling shall be based on the Valence-Arousal Circumplex described in Figure 2. This shall be validated by a group of psychologists. Once selected, the dataset can now undergo pre-processing where they are 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, cropping, and color conversion of the images. This is conducted to reduce the model's computational complexity and improves training efficiency. Furthermore, the processed data will be input for a CNN model.

Convolutional Neural Networks with Binary Classification: The CNN model will include a layer that performs convolutions with 32 size filters (3,3). A dropout layer with a rate of 0.2 will be used to prevent overfitting. The model will flatten the resulting 2D features into a 1D feature vector. In addition, a dense layer with 128 units and ReLU activation will be added. A MaxPooling layer of size (2,2) will also be included. The output layer shall be a binary classification, distinguishing between a panic attack and non-panic attack patterns from the visual input data.

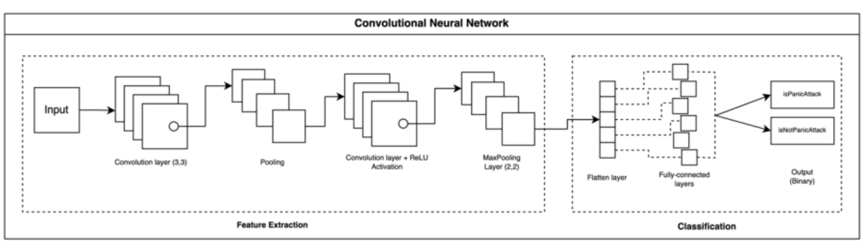

Figure 3: FER-CNN Model for classifying binary output

Model training and evaluation: The dataset will be split into a training and testing set where the former shall be used to train the CNN model and the latter used to evaluate the model's performance. The annotated dataset shall be balanced with the FER2013 dataset to ensure a diverse range of emotions and prevent biases. Evaluation metrics such as accuracy, precision, recall, F1 score, confusion matrix, mean of absolute error, and mean squared error, will be used to measure the performance of the developed CNN model.

Model interpretation: The dataset testing framework illustrates 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 shall recognize patterns from a real-time video capture. However, due to ethical considerations, this study aims to test the developed model in a simulated environment that closely mimics a telemedicine environment. In this case, this study will create 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 serves as a substitute for a telemedicine environment since it replicates the functionalities and interaction characteristics of a telemedicine: participants must be facing their laptop screen while being recorded by a web camera. This approach will help facilitate 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.

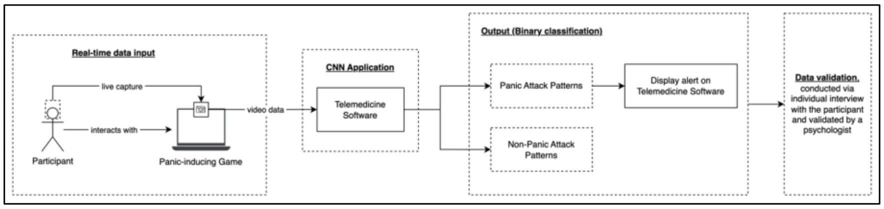

Figure 4: FER-CNN Model real-world testing framework

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. Both patients and psychologists can use the application.

Figure 5: Low-fidelity wireframe and interface design for the telemedicine application

3.5 Conceptual Framework

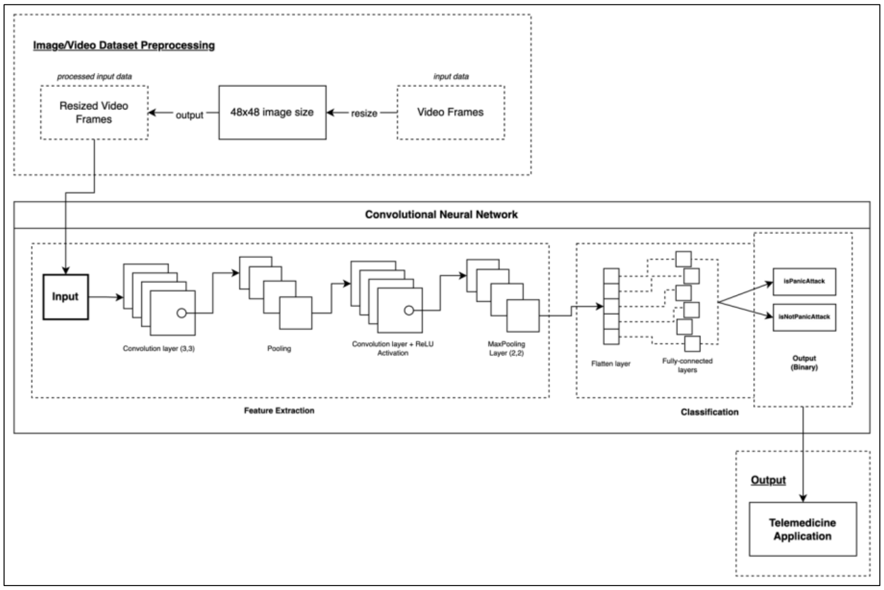

Figure 6: Conceptual framework for the FER-CNN model

Described in Figure 1 is the conceptual framework for the hybrid CNN model to be developed in this study. The model shall accept visual data, particularly video recordings of a patient during a psychotherapy session, as input. Before the CNN model processes the data, it shall undergo pre-processing where, for instance, the visual data will be extracted from video frames, resized, and cropped into the desired dimension of 48x48. The processed data will be used as input for the CNN model. The CNN model shall have a convolutional layer with 32 filters of size (3,3), a dropout layer with 0.2 rates to reduce its overfitting tendencies, a flattened layer to convert the 2D features into a 1D feature vector, a dense layer with 128 units and Rectified Linear Unit (ReLU) activation (expressed as f(x)

= max(0, x)), and a MaxPooling layer of size (2,2). The output layer shall be a binary classification of a panic attack or a non-panic attack pattern for the visual input data.

REFERENCES

Ahmed, T., Wahid, M. F., & Hasan, M. J. (2019). Combining Deep Convolutional Neural Network with Support Vector Machine to Classify Microscopic Bacteria Images. 2nd International Conference on Electrical, Computer and Communication Engineering, ECCE 2019, 1–5. https://doi.org/10.1109/ECACE.2019.8679397.

Association Staff, A. P. (2013). Diagnostic and Statistical Manual of Mental Disorders - DSM-5.

Badrulhisham, N. A. S., & Mangshor, N. N. A. (2021). Emotion Recognition Using Convolutional Neural Network (CNN). *Journal of Physics: Conference Series*, *1962*(1). https://doi.org/10.1088/1742-6596/1962/1/012040

Barlow, D. H., & Craske, M. G. (2022). Mastery of Your Anxiety and Panic: Workbook.

Cordero Jr, D. A. (2022). Telehealth during the COVID-19 pandemic in the Philippines. *Journal of Public Health (United Kingdom)*, *44*(3), E429–E430. https://doi.org/10.1093/pubmed/fdab273

Cornejo, J. Y. R., & Pedrini, H. (2019). Audio-Visual Emotion Recognition Using a Hybrid Deep Convolutional Neural Network based on Census Transform. Conference Proceedings - IEEE International Conference on Systems, Man, and Cybernetics, 2019-Octob, 3396–3402. https://doi.org/10.1109/SMC.2019.8914193

De Guzman, M. R. Q., Ordoñez, J. L. N., Somocierra, R. O., & Fuentes, G. S. (2021). *Online Scheduling System for Doctors and Patients in a Hospital*. *21*, 1730–1741.

Deopa, A., Sinha, A., Prakash, A., & Sinha, R. K. (2019). Facial Expression Recognition using Convolutional Neural Network and SoftMax function on Captured Images. Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019, Icces, 273–279. https://doi.org/10.1109/ICCES45898.2019.9002524

Divya Meena, S., & Agilandeeswari, L. (2019). An Efficient Framework for Animal Breeds Classification Using Semi-Supervised Learning and Multi-Part Convolutional Neural Network (MP-CNN). IEEE Access, 7, 151783–151802. https://doi.org/10.1109/ACCESS.2019.2947717

Dunne, J.E., & Domakonda, M. (2019). Expanding Pediatric Mental Health Treatment Through. *Journal of the American Academy of Child & Adolescent Psychiatry,* 10-14

França, J. M. S., & Soares, M. S. (2015). SOAQM: Quality model for SOA applications based on ISO 25010. *ICEIS 2015 - 17th International Conference on Enterprise Information Systems, Proceedings*, *2*, 60–70. https://doi.org/10.5220/0005369100600070

Freire, R. C., Ferreira-Garcia, R., Cabo, M. C., Martins, R. M., & Nardi, A. E. (2020). Panic attack provocation in panic disorder patients with a computer simulation. *Journal of Affective Disorders, 264,* 498–505. https://doi.org/10.1016/j.jad.2019.11.081

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning.

Hameed, N., Shabut, A. M., & Hossain, M. A. (2019). Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine. International Conference on Software, Knowledge Information, Industrial Management and Applications, SKIMA, 2018-Decem, 1–7. https://doi.org/10.1109/SKIMA.2018.8631525

Hasan, M. K., Aleef, T. A., & Roy, S. (2020). Automatic Mass Classification in Breast Using Transfer Learning of Deep Convolutional Neural Network and Support Vector Machine. 2020 IEEE Region 10 Symposium, TENSYMP 2020, June, 110–113. https://doi.org/10.1109/TENSYMP50017.2020.9230708

Heesacker, M., Perez, C., Quinn, M. S., & Benton, S. (2020). Computer-assisted psychological assessment and psychotherapy for collegians. *Journal of Clinical Psychology*, *76*(6), 952–972. https://doi.org/10.1002/jclp.22854

Hewitt, O. M., Tomlin, A., & Waite, P. (2021). The experience of panic attacks in adolescents: an interpretative phenomenological analysis study. *Emotional and Behavioural Difficulties*, *26*(3), 240–253. https://doi.org/10.1080/13632752.2021.1948742

Kartali, A., Roglic, M., Barjaktarovic, M., Duric-Jovicic, M., & Jankovic, M. M. (2018). Real-time Algorithms for Facial Emotion Recognition: A Comparison of Different Approaches. *2018 14th Symposium on Neural Networks and Applications, NEUREL 2018*, 1–4. https://doi.org/10.1109/NEUREL.2018.8587011

Lally, J., Tully, J., & Samaniego, R. (2019). Mental health services in the Philippines.

BJPsych International, 1–3. doi:10.1192/bji.2018.34

Lang, P. J. (1995). The Emotion Probe. *American Psychologist Association*, *50*(5), 372–385. https://doi.org/10.1037/0003-066X.50.5.372

Law-Ay, S., Fermil, F. A., & Agod, J. M. (2022, June 19). Kumusta ka? Challenges, mental health and well-being assessment among DNSC employees during the COVID-19 pandemic. *Davao Research Journal*. https://doi.org/10.59120/drj.v13i1.2

LeCun, Y., & Bengio, Y. (1995). Convolutional Networks for Images, Speech, and Time-Series.

Liliana, D. Y. (2019). Emotion recognition from facial expression using deep convolutional neural network. *Journal of Physics: Conference Series*, *1193*(1), 0–5. https://doi.org/10.1088/1742-6596/1193/1/012004

Markina, O. S. (2021). The Experience of Distant Psychological Help Organization in Telemedicine During COVID-19 epidemic. CEUR Workshop Proceedings, 3090, 382–390

Martinez, A. B., Co, M., Lau, J., & Brown, J. S. L. (2020). Filipino help-seeking for mental health problems and associated barriers and facilitators: a systematic review. Social Psychiatry and Psychiatric Epidemiology. doi:10.1007/s00127-020-01937-2

Matsumoto, K., Sutoh, C., Asano, K., Seki, Y., Urao, Y., Yokoo, M., Takanashi, R., Yoshida, T., Tanaka, M., Noguchi, R., Nagata, S., Oshiro, K., Numata, N., Hirose, M., Yoshimura, K., Nagai, K., Sato, Y., Kishimoto, T., Nakagawa, A., & Shimizu, E. (2018). Internet-based cognitive behavioral therapy with real-time therapist support via videoconference for patients with obsessive-compulsive disorder, panic disorder, and social anxiety disorder: Pilot single-arm trial. *Journal of Medical Internet Research*, *20*(12), 1–17. https://doi.org/10.2196/12091

Mehrotra, A., Ray, K., Brockmeyer, D., Barnett, M., & Bender, J. A. (2020). Rapidly Converting to "Virtual Practices": Outpatient Care in the Era of Covid-19. *NEJM Journal*.

Noceda, A. V. G., Acierto, L. M. M., Bertiz, M. C. C., Dionisio, D. E. H., Laurito, C. B. L., Sanchez, G. A. T., & Loreche, A. M. (2023). Patient satisfaction with telemedicine in the Philippines during the COVID-19 pandemic: a mixed methods study. *BMC Health Services Research*, *23*(1), 1–12. https://doi.org/10.1186/s12913-023-09127-x

Pan, Y., Fu, M., Cheng, B., Tao, X., & Guo, J. (2020). Enhanced deep learning assisted convolutional neural network for heart disease prediction on the internet of medical things platform. *IEEE Access*, *8*, 189503–189512. https://doi.org/10.1109/ACCESS.2020.3026214

Pranav, E., Kamal, S., Satheesh Chandran, C., & Supriya, M. H. (2020). Facial Emotion Recognition Using Deep Convolutional Neural Network. 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 317–320. https://doi.org/10.1109/ICACCS48705.2020.9074302

Rai, S., Raut, A., Savaliya, A., & Shankarmani, R. (2018). Darwin: Convolutional Neural Network based Intelligent Health Assistant. *Proceedings of the 2nd International Conference on Electronics, Communication and Aerospace Technology, ICECA*

2018, Iceca, 1367–1371. https://doi.org/10.1109/ICECA.2018.8474861

Record, J. D., Ziegelstein, R. C., Christmas, C., Rand, C. S., & Hanyok, L. A. (2021). Delivering personalized care at a distance: How telemedicine can foster getting to know the patient as a person. *Journal of Personalized Medicine*, *11*(2), 1–11. https://doi.org/10.3390/jpm11020137

Roncero, C., García-Ullán, L., de la Iglesia-Larrad, J. I., Martín, C., Andrés, P., Ojeda, A., González-Parra, D., Pérez, J., Fombellida, C., Álvarez-Navares, A., Benito, J. A., Dutil, V., Lorenzo, C., & Montejo, Á. L. (2020). The response of the mental health network of the Salamanca area to the COVID-19 pandemic: The role of the telemedicine. *Psychiatry Research*, *291*(June), 113252. https://doi.org/10.1016/j.psychres.2020.113252

Stijelja, S., & Mishara, B. L. (2020b). COVID-19 and Psychological Distress—Changes in internet searches for mental health issues in New York during the pandemic. *JAMA Internal Medicine*, *180*(12), 1703. https://doi.org/10.1001/jamainternmed.2020.3271

Valdes, B., Salani, D., King, B., & De Oliveira, G. C. (2021). Recognition and Treatment of Psychiatric Emergencies for Health Care Providers in the Emergency Department: Panic Attack, Panic Disorder, and Adverse Drug Reactions. *Journal of Emergency Nursing*, *47*(3), 459–468. https://doi.org/10.1016/j.jen.2021.01.004

Victor, A. M. (2019). Telepsychiatry and comprehensive mental health India. *Perspectives in Psychiatric Care*, *55*(3), 459–463. https://doi.org/10.1111/ppc.12342

Xin, R., Zhang, J., & Shao, Y. (2020). Complex Network Classification with Convolutional Neural Network. Tsinghua Science and Technology, 25(4), 447–457. https://doi.org/10.26599/TST.2019.9010055

Yuduang, N., Ong, A. K. S., Vista, N. B., Prasetyo, Y. T., Nadlifatin, R., Persada, S. F., Gumasing, M. J. J., German, J. D., Robas, K. P. E., Chuenyindee, T., & Buaphiban, T. (2022). Utilizing Structural Equation Modeling–Artificial Neural Network hybrid approach in determining factors affecting perceived usability of mobile mental health application in the Philippines. *International Journal of Environmental Research and Public Health*, *19*(11), 6732. https://doi.org/10.3390/ijerph19116732

Zahara, L., Musa, P., Prasetyo Wibowo, E., Karim, I., & Bahri Musa, S. (2020). The Facial Emotion Recognition (FER-2013) Dataset for Prediction System of Micro-Expressions Face Using the Convolutional Neural Network (CNN) Algorithm based Raspberry Pije. *2020 5th International Conference on Informatics and Computing, ICIC 2020*, *7*. https://doi.org/10.1109/ICIC50835.2020.9288560

Zargaran, D., Walsh, C., Koumpa, F. S., Ashraf, M. A., White, A. J., Patel, N., Tanna, R., Trepekli, A., & Zargaran, A. (2020). Comment on "internet-based cognitive behavioral therapy with real-time therapist support via videoconference for patients with obsessive-compulsive disorder, panic disorder, and social anxiety disorder: Pilot single-arm trial." *Journal of Medical Internet Research*, *22*(8), 1–2.

https://doi.org/10.2196/13234