

AI Driven Emotion Recognition: Leveraging IoT Sensors and Machine Learning for Early Detection of Psychological Disorders

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ABSTRACT

The rapid development of Artificial Intelligence (AI) and Machine Learning (ML) approaches has significantly improved the mental health surveillance systems, particularly through emotion recognition. Facial expression recognition, a crucial part of affective computing, has been identified as a reliable method of assessing emotional conditions, which are crucial indicators of Psychological Disorders. ML could offer real-time and non-invasive surveillance solutions. This study analyzes AI and the Internet of Things (IoT) use in facial recognition to identify emotions and their role in enhancing mental health surveillance systems. The study highlights the importance of leveraging large annotated datasets and the roles of the Convolutional Neural Networks (CNNs) to increase detectability. The face recognition challenges, such as changing lighting conditions, facial obstruction, and cultural differences in expressing emotions, and the methods provided by AI algorithms to overcome them are also discussed – psychological Disorders. Emotion detection methods can improve the detection of the disorder early, provide custom-made treatment plans using the IoT sensor, and enable continuous monitoring of a patient's psychological well-being.

KEYWORDS: Artificial Intelligence; Emotion Recognition; Internet of Things; Convolutional Neural Networks; Facial Expression Recognition; Mental Health Monitoring.

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INTRODUCTION

Emotion plays a significant role in daily lives, impacting thoughts, reactions, and behaviors (Brosch, 2021). It is part of decision-making, problem-solving, communication, and negotiation in most situations. Emotion is a state of mind that varies and is commonly accompanied by physiological changes, expressed through external body symptoms and manifested through internal feelings (Jones et

al., 2023). Monitoring such changes may support the identification of potential psychological or emotional difficulties, particularly in individuals who require mental health monitoring. One such method is emotion recognition, which refers to the identification and classification of observable human emotional states (Lin et al., 2023). Images or chains of images are obtained as the input signals. They are processed through feature extraction and classification techniques. Emotions, such as happiness, sadness, anger,

and stress, fluctuate across various locations, situations, cultures, settings, and individual personalities and interests. Emotion recognition investigates and creates systems that detect how an individual feels to identify these feelings (García-Hernández et al., 2024). This is essential for advancing various sensor applications, whereby devices can capture human physical characteristics and convert these data into computational messages that convey distinct human emotions in real-time. For example, the illumination in a room is adjusted according to an individual's mood, or teaching techniques might be enhanced by analyzing pupils' gestures. Emotion recognition has emerged as a novel trend in digital advertising. Corporations have adeptly utilized this technology to entice more consumers by aligning with their preferences for product advertising.

The advancement of sensor networks, Internet of Things (IoT) technologies, and wearable smart devices enables the rapid and effective detection of many human emotions (Xu et al., 2024). This has become an important area of research in large-scale networks, particularly for human-machine interaction. If robots could comprehend people's affective emotional states, communication would be far more seamless and efficient. Emotion recognition can be performed using diverse modalities and methodologies, including physiological signals, facial expressions, speech, text, and body movements (Jemiolo et al., 2022). Common modalities include written text, speech, physical movements, facial expressions, and body language. This is achieved by producing IoT sensors specific to requirements and demands, and they can instantly interact with the human body (invasive) or non-invasively (non-invasive) to gather physiological information (Panda et al., 2024).

Emotion recognition is essential for human health and the medical processes used to identify, evaluate, and assess an individual's medical status (Suhaimi et al., 2020). It is increasingly being investigated for monitoring changes in physiological and emotional states. It is a common occurrence that consumers' emotions influence how they make decisions. Under pleasant situations, perception will tend to incline itself towards positive events, and vice

versa, with negative feelings potentially causing health problems. IoT sensors collect physiological data and send it to a computer system for analysis (Ribeiro et al., 2023). The most common technology employed in communication is ZigBee. This helps in relaying information from the IoT sensors to the computing systems. Application Programming Interface (API) helps to track and administer real-time data (Pérez-Jorge et al., 2025). Under pleasant situations, perception will tend to incline itself towards positive events, and vice versa, with negative feelings potentially causing health problems.

RELATED WORKS

By gathering data about personal feelings and behavior with the help of smart wearables and other data collection methods, Artificial Intelligence (AI) can effectively predict personal mental health-related issues (Olawade et al., 2024). Although the use of AI is long-standing, the study has not adequately discussed the practical application of AI in mental health and psychological therapies. AI has potential applications in healthcare for supporting assessment, monitoring, and delivery of services to individuals experiencing mental health difficulties.

Numerous studies have proved that applying the idea of Machine Learning (ML) to psychological treatment is essential, as it will allow evaluating the symptoms associated with mental disorders actively and objectively to help diagnose and provide therapy (Patibandla et al., 2025). Previous studies have investigated AI-based approaches for supporting mental health assessment, monitoring, and intervention. Rathnayaka et al. introduced an emotional support chatbot with cognitive capabilities to deliver continuous emotional support, personalized assistance, and remote mental health monitoring (Rathnayaka et al., 2022). Xu et al. (2023) investigated the use of machine learning in relation to depressive conditions among employees. Joshi et al. (2022) investigated the use of artificial intelligence and natural language processing for detecting depression-related information in Twitter feeds. Kolenik (2022) described a mobile application designed to provide psychological interventions

for stress management based on behavioral theory (Rajeswari et al., 2024).

Some studies stressed the importance of applying AI to monitor mental health through innovative Internet of Things [IoT] gadgets. Mandal et al. (2023) discussed the collection of physiological data using AI-based wearable devices for monitoring aspects of mental health. McNaboe et al. (2022) developed and validated a multimodal wearable device for simultaneous collection of electrocardiogram (ECG), electromyogram (EMG), and electrodermal activity (EDA). They then processed the data with the help of the Support Vector Machine (SVM) to determine individual stress levels. AlArnaout et al. (2025) investigated the use of wearable sensors and machine learning for physiological monitoring. investigated the use of smart devices and physiological information for the prediction of mental fatigue. The researchers employed smart gadgets to collect the variability of a person's heart rate and applied ML to predict mental fatigue. Jolly et al. (2025) examined the association between college students' academic performance, sleep quality, perceived stress, and mental health using wearable devices and mobile phones. These parameters are a significant indicator of the mental health of a pupil.

Research indicates that human emotions are closely linked to cognitive judgments, significantly influencing social and cultural activity and communications. Numerous efforts have been undertaken to identify emotions and label them according to multiple factors such as mood, sentiment, and effect. Revina et al. (2021) discussed the categorization of human emotions based on facial expressions. The reviewed literature describes several approaches to categorizing emotions from facial expressions, including commonly studied basic emotional categories such as happiness, sadness, fear, surprise, anger, and contempt. The reviewed literature also considers additional emotional states beyond commonly studied basic categories.

Kang et al. (2021) categorized human emotional states into groups based on brain-wave-related indicators, including motivating, basic, and self-

conscious emotions. The studies have shown that emotion is an essential part of the everyday decision-making process. Studies show that emotions are important in expansive attention and creating cognitive, physical, and social resources. This will help improve people's physical, social, and intellectual abilities. Bala et al. (2022) examined emotion classification in the context of an e-learning environment. A total of 65 emotions are categorized. These are divided into two categories, namely, primary emotions and other feelings. The former deals with the basic emotions, including 10 emotions, such as wrath and joy, and the latter, which deals with the other feelings, includes the other 58 emotions. Other studies classify emotions based on vocal and physical cues.

Emotions are significant in the startup, accomplishment, and control of actions. It is a significant concern to analyze human feelings, their successful detection (response), and tracking (the effect of response on an individual, both physically and psychologically).

PROPOSED AI-DRIVEN EMOTION RECOGNITION

This section shows an AI-based Emotion Recognition Method (AI-ERM) of emotion classification using Convolutional Neural Networks (CNN) (Sarvakar et al., 2023). The proposed approach involves model selection, hyperparameter optimization, and training of CNN architectures, including VGG and ResNet models. The framework is intended to support facial-image processing and emotion classification. The proposed AI-ERM method includes an autoencoder to effectively decode and select features to optimize the efficiency of the picture classification system.

Logical Architecture

The suggested AI-ERM system has three layers: (i) Cloud Tier, (ii) Fog Tier, and (iii) IoT Tier. The primary levels are: (i) IoT and (ii) Fog. In IoT, a suggested mobile application captures a picture using the smart device and then transmits this facial image to the fog Tier. In the fog Tier, a controller exists, the Fog Server (FS), tasked with acquiring the facial picture and identifying the emotion based on the suggested ML approach. The Fog Tier includes a database that houses the

pretrained datasets. Following emotion classification, the fog server is described as transmitting an alert to the associated device when predefined emotional categories, such as anger, fear, sadness, or surprise, are identified.

The primary control and management occur at the fog Tier controller to reduce communication latency and support near-real-time emotion classification. The suggested architecture is displayed in Figure 1.

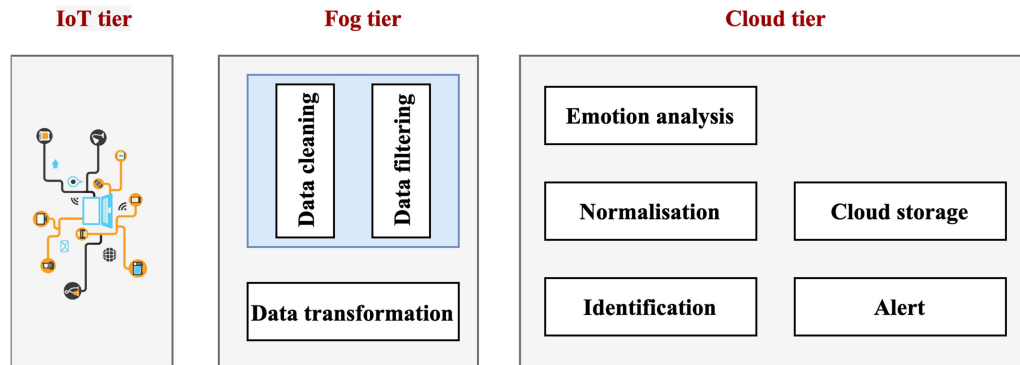


Figure 1: Logical architecture of the AI-ERM

IoT Framework

The suggested AI-ERM uses sensory information readily acquired using a specially

designed wearable. The IoT model facilitates seamless data transmission from the sensors to the hub and cloud server, as shown in Figure. 2.

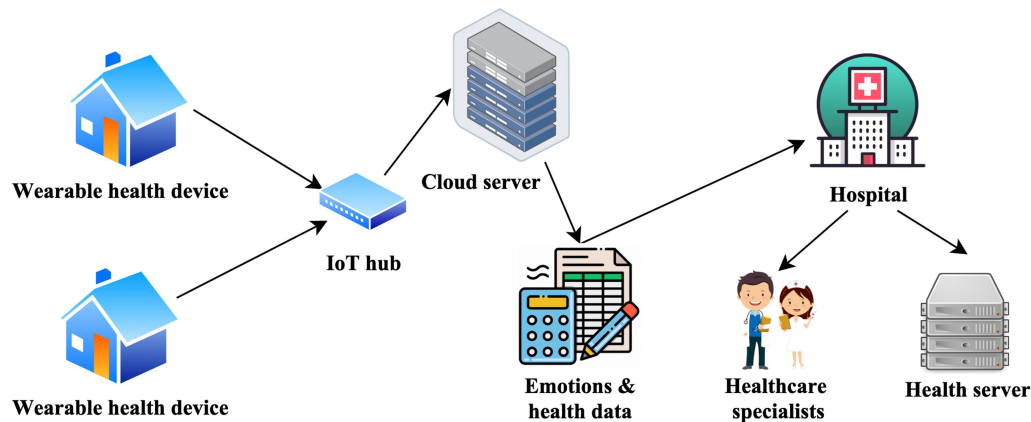


Figure 2: IoT architecture of the AI-ERM

According to the proposed IoT configuration, each sensor generates 16-bit samples at a sampling frequency of 1 kHz. Every sensor needs a data speed of 16 kbps. The AI-ERM system requires eight sensors, each measuring 16 bits and operating at a sample frequency of 1 kHz, thereby requiring a transmission rate of 128 kbps. An additional 64 kbps is allocated in the proposed communication configuration for future modifications, upgrades, and additional IoT sensors. Delay is the most important factor in this case, as the sampling period is 1 ms;

therefore, each data sample has to be delivered within less than 1 ms to achieve the IoT hub. Time-Division Multiple Access (TDMA) is proposed to organize communication among multiple sensors and reduce the possibility of temporal overlap between transmissions. Sensing to the IoT hub is carried out in a 10-ms superframe. Each superframe is partitioned into 15 intervals, whereby each timeslot of the interval is 400 microseconds. The transmission overhead duration is 3.85 ms inside a superframe. Given the implementation of

TDMA, the IoT hub transmits a radio signal at the commencement of each superframe to rectify imprecise local clock synchronization and, if

necessary, coordinate messages from various sources to prevent temporal overlap.

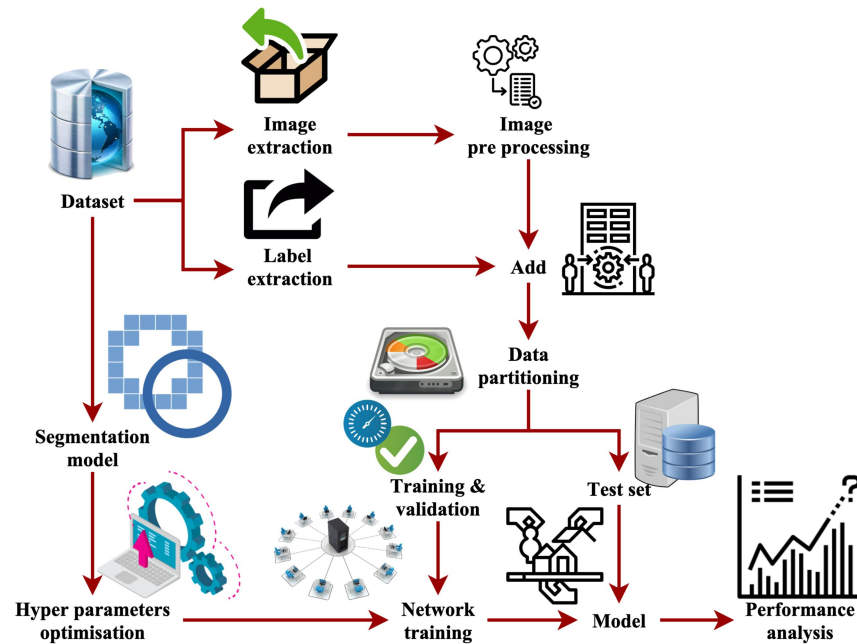


Figure 3: Workflow of the AI-ERM

Research Design and Structure

The approach for emotion identification in mental health monitoring focuses on creating a computer system that can precisely identify facial movements in real-time and correlate those movements with feelings as shown in Figure 3. In this system, CNNs are used to recognize faces and emotions, which are widely used for image classification and can be applied to facial images containing variations in illumination, pose, and facial expression. The system is configured to accept video frames or photos, identify faces, and categorize the corresponding emotions according to the facial features, enabling real-time emotional tracking in psychological monitoring programs.

The AI-ERM system consists of many important operations: facial recognition, facial landmark recognition, emotion recognition, and output analysis. Face identification is one technique for identifying the face in a video stream or a picture. At the same time, facial feature recognition makes the model fit in remarkably. It recognizes the important facial features such

as eyes, mouth, and eyebrows, which are essential in properly characterizing emotions.

The CNN models process facial-image data to classify the emotional categories defined in the dataset, including happiness, sadness, anger, surprise, fear, and neutral or other dataset-specific categories. The resultant outcome is then applied to gain a clue into the emotional state of the individual in question, potentially providing additional information for professionals involved in mental health monitoring.

The purpose of this computational system is to be easily introduced to existing medical systems to allow remote monitoring of patients, so the doctors can constantly monitor their patients' feelings without having direct contact with them or providing any medical treatment. The proposed approach aims to support patient monitoring by facilitating the observation of emotional states; clinical diagnosis and treatment decisions remain the responsibility of qualified healthcare professionals. The purpose of this computational system is to be easily introduced to existing medical systems to allow

remote monitoring of patients (Surekha et al., 2024).

Data Acquisition

Data Sources

The data collection strategy is critical to forming a powerful emotion detection model. The data sets used in the model's training contain the viewable collections of reputable facial emotion detection, such as VGG and ResNet, which provide huge volumes of annotated photographs of human faces with various feelings. The dataset comprises 35,000 facial images categorized into seven emotional classes: anger, disgust, fear, happiness, sadness, surprise, and neutral. This data is popular in emotion detection studies due to its diversity in age, gender, and ethnicity. It offers a strong foundation for developing models generalized to most demographic groups. These data provide the basis for training and evaluating the CNN-based facial emotion recognition system. The datasets ensure the model is exposed to diverse data and can handle changes in facial expressions due to cultural differences, age, and environmental conditions (Rajeswari et al., 2024).

Data Preprocessing

- Data preparation

It is a necessary stage of ensuring the quality and standardization of the data prior to feeding it into the framework. The first processing pipeline comprises numerous cleaning, normalization, and enrichment steps.

⇒ Data Cleaning

The initial step is to discard the imperfect or unfinished photographs in the collection. Those images do not have real faces or are highly distorted to ensure that only good and valuable data can be added in the training process.

⇒ Normalization

It is done to ensure that the pixel value of every picture falls within a similar range. It is often the process of normalizing the pixel values to the range of 0-1 or standardizing them to give an average of zero and a standard deviation of one. Normalization improves model convergence in

the training process because the inputs are kept in a uniform scale.

⇒ Facial alignment

It is an important pre-processing step involving emotion identification as it allows the model to focus on important facial features, including the eyes, nose, and mouth, which are fundamental in emotion identification. Face alignment involves the identification and extraction of faces in images; then, the geometry is used to normalize the placement of the faces.

- Scaling and Augmentation

The CNN model accepts images that are converted to a standard input size. Also combined with resizing is the synthetic enlargement of the variety of the training dataset through data augmentation methods, like random rotations, translations, flips, and luminance adjustments. Augmentation is used to generalize the model in reality through modeling the change in location, lighting, and facial expression. Such preprocessing steps ensure the data is optimized to improve the CNN model's work and minimize overfitting and bias.

- Data Partitioning and Validation:

The available image data are divided into training, validation, and testing subsets according to the experimental configuration.

In order to reasonably ascertain the effectiveness of the model, the data set will be partitioned into three subsections: training, validation, and assessment. Training the algorithm is done on the training group, the hyperparameters are optimized on the validation set, a model is selected, and the final efficiency of the trained system is evaluated using the testing group.

The data is conventionally divided into an 80:10:10 ratio, 80 per cent is used in training, 10 per cent in verification, and 10 per cent in testing. The resilience and generality of the model using K-fold cross-validation are calculated with the help of cross-validation and other techniques. Cross-validation reduces overfitting, and the model's effectiveness does not change when used with several data fragments.

CNN Architecture

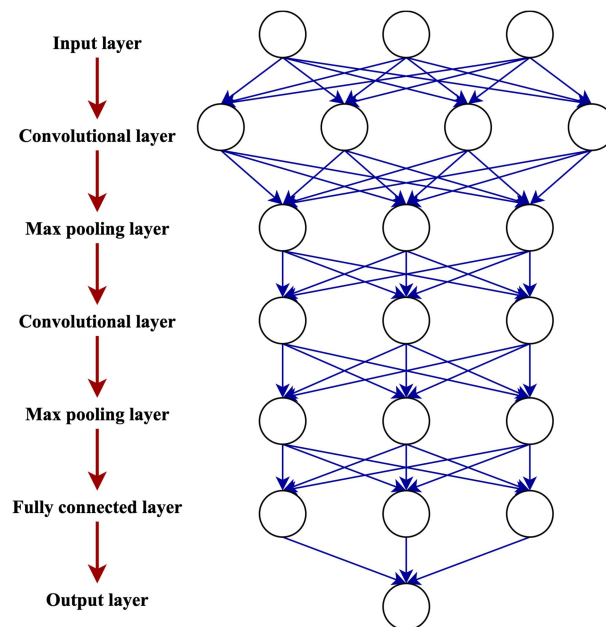


Figure 4: CNN architecture for AI-ERM

The CNNs are used to identify emotions because they are effective for picture categorization. CNNs use hierarchical feature representations in which successive layers learn increasingly complex visual features for facial-image classification, as represented in Figure 4 (Dharamjit et al., 2024; Rajeswari et al., 2024).

- Convolutional Tiers

It performs the fundamental feature extraction processing, which includes convolutional filtering of the input pictures. The filters compare the image in terms of its features, including edges, texture, and other features, which are significant in the recognition of facial emotions. Since the network is in progress, the filters can distinguish finer details, like the eyes, the shape of the mouth, and the general shape of the facial features.

- Pooling Tiers

It shrinks the image's geometrical dimensions and preserves the highly required data. This action reduces the cost of computing in the network. It makes the model less vulnerable to minor alterations in the input data, including a variation in location or direction.

- Fully Connected Tiers

The attributes are churned through the completely interconnected layers after the convolutional and pooling levels, which do the final classification. These layers combine the extracted features to produce class-specific predictions for the emotional categories defined in the dataset.

- Activation Features

Rectified Linear Unit (ReLU) is an activation function in CNN since it allows learning and non-linearity. The output in the final level is the probability of each class, which is achieved through the softmax activation.

Model Training

The CNN model is associated with many processes associated with the learning process, including hyperparameter optimization, modification, and normalization. The principal hyperparameters considered in model training include the learning rate, batch size, and number of training epochs. Optimization methods, such as Adam and Stochastic Gradient Descent (SGD), reduce the loss function, often a category-based cross-entropy loss function for

problems with multiple classes. Regularization approaches, like dropout, mitigate overfitting by randomly deactivating specific neurons during training, compelling the model to acquire more resilient characteristics.

Systemic Integration for Mental Health Surveillance

The AI-ERM model is implemented into a psychological surveillance scheme in real-time by deploying it as a software program that takes real-time footage or photos. It was developed to track the emotions of individuals and provide notifications when significant changes in the emotional state were observed. The approach could yield some instances of intense discomfort, like sudden increases in distasteful emotions, which indicate a crisis of psychological health.

RESULTS AND DISCUSSIONS

The primary input of the article is the evaluation of the AI model in detecting Psychological Disorders with a facial expression database, with the help of automated methods. It aims to make an adequate assessment of the proposed AI-ERM system based on image modalities possible, provided the utility of AI in medical imaging guidelines is assessed. The analysis aims to analyze the performance indicators and the convergence capability test. Analysis of performance indicators will involve the Accuracy, Recall, Precision, and F-score dimensions.

This research primarily focused on recall, accuracy, precision, and convergence capability in recognizing facial expression-based Psychological Disorders. The evaluation of the applied metrics and the subsequent comparison of the model outcomes of this research provide a strong basis for more reliable and practical clinical application in the recognition of

Psychological Disorders. However, more sophisticated evaluation indicators lead to a more in-depth performance assessment, particularly in medical diagnostics, when performance outcomes regarding recall and accuracy are paramount.

All tests and analyses will be done using a desktop computer with the following specifications: 10th Gen Intel i7, eight cores, 64.0 GB of RAM, 2 TB of storage space, and an NVIDIA graphics card. The analysis relies on the data ratio setup and corresponding data enrichment approaches. The convergence ability test is carried out by analyzing the loss function and the time taken in the execution. This is implemented in line with the appended data augmentation process.

Utilized dataset

This study employs a collection of curated facial photographs depicting various emotional states in autistic children from India. The replicated and stock photos have been deleted. The database has been classified into six facial-emotion categories: anger, fear, happiness, neutral, sadness, and surprise. The study utilized 780 images for training (anger: 70, fear: 40, happiness: 300, neutral: 50, sadness: 250, and surprise: 70) and 100 images for testing (anger: 10, fear: 10, happiness: 50, neutral: 10, sadness: 10, and surprise: 10).

Performance metrics

Figure 5 displays the performance assessment of the different CNN architectures for facial emotion classification. The three designs (VGG-16, ResNet-50, and ResNet-101) exhibited different training, verification, and testing rate configurations. The mode of performance assessment depends on the data structure and the data augmentation process.

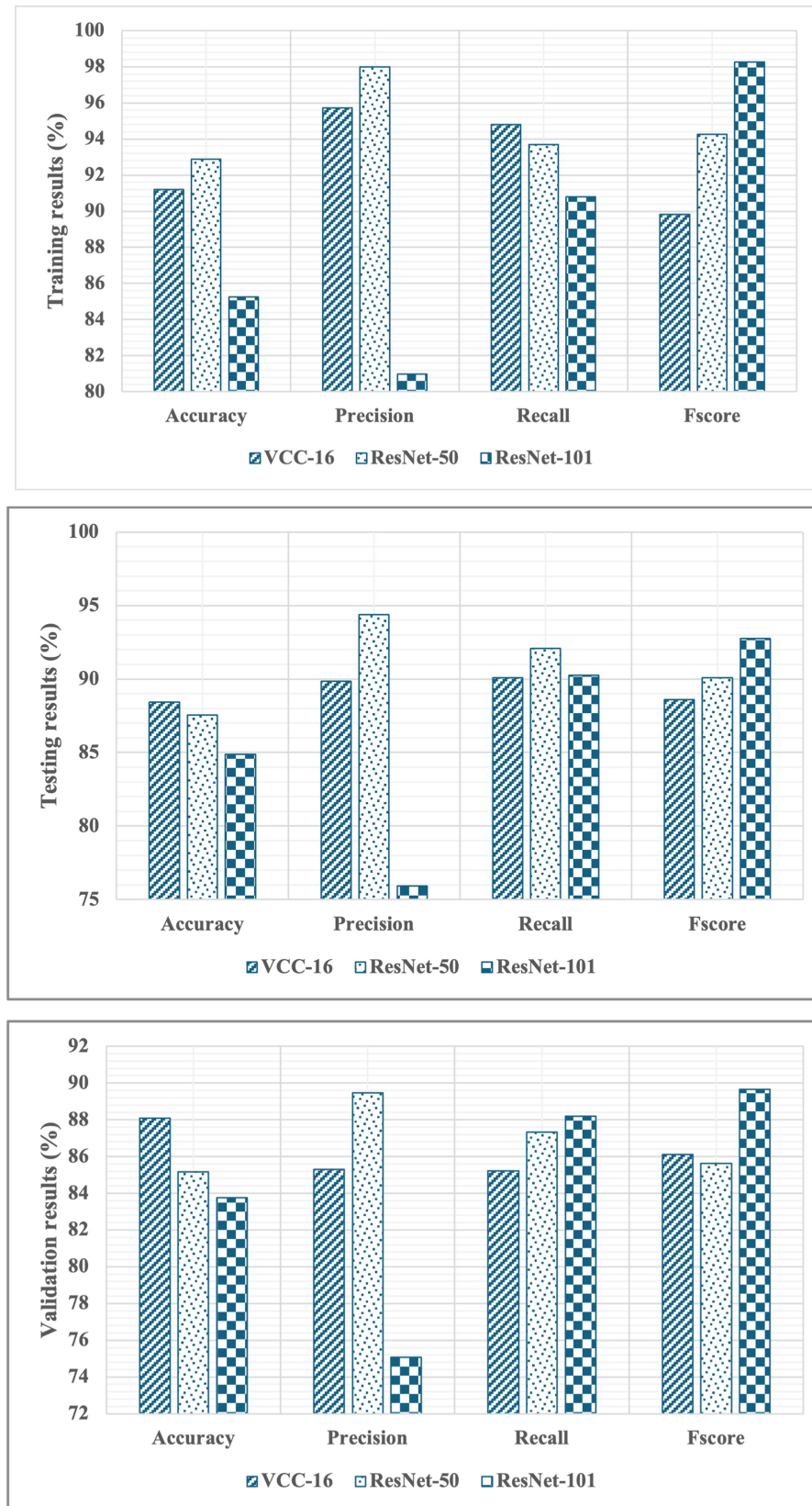


Figure 5: Performance analysis (a) Training (b) Testing (c) Validation

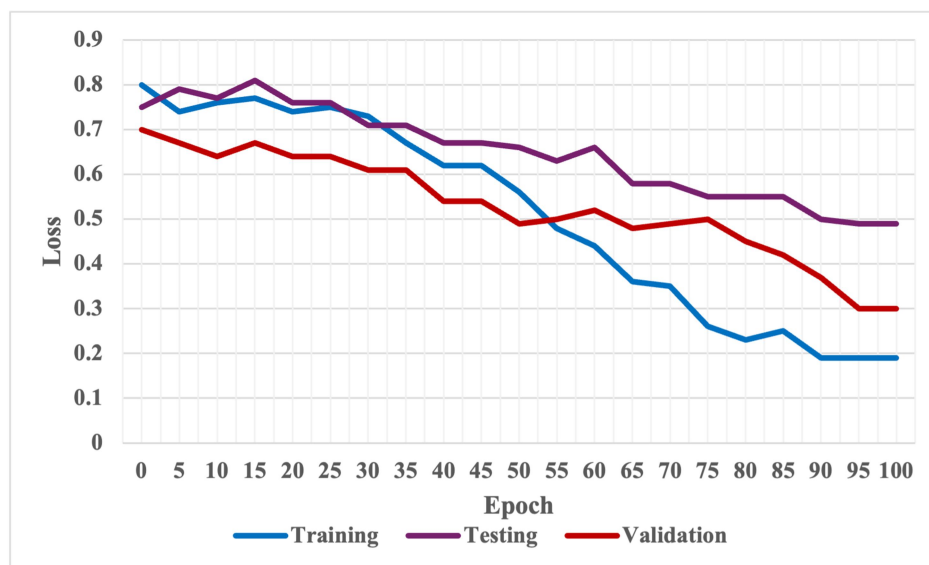
In addition to the data configuration, the augmentation procedure constantly enhances the efficacy measure derived from the original dataset. The augmentation procedure improved the reported performance measures, with increases in accuracy, recall, precision, and F-score of 6%, 12%, 4%, and 3%, respectively. An enhancement in recall signifies a reduction in the incidence of false negatives. False negatives in medical practice are rigorously avoided. Improvements in accuracy exert a substantial influence on medical domains. Enhanced recall of automated Psychological Disorders diagnosis will increase awareness and timely intervention. It will substantially improve the development and quality of life of individuals with Psychological Disorders in the following years. This measure varies somewhat between the original and augmented data, contingent upon the training, validation, and testing datasets. Increasing the proportion of augmented training data resulted in changes in the reported

performance measures, with average improvements of 5% in accuracy, 6% in recall, 4% in precision, and 6% in F-score.

This continual enhancement transpires along with augmented data. The outcome indicator aims to diminish with an increased training data ratio, showing only slight improvement. The average accuracy declines to 0.85%, while precision diminishes to 3.7%. The volume of enhanced data is quintuple the original data. Augmenting the training data proportion on large datasets often diminishes the generalization performance. The efficiency of the metric is likely to decrease.

Convergence Assessment

The study focuses on augmenting the effects of the improvement of converging capabilities. Figure 6 depicts the convergence path of the concerned AI design, based on baseline data and augmented data.



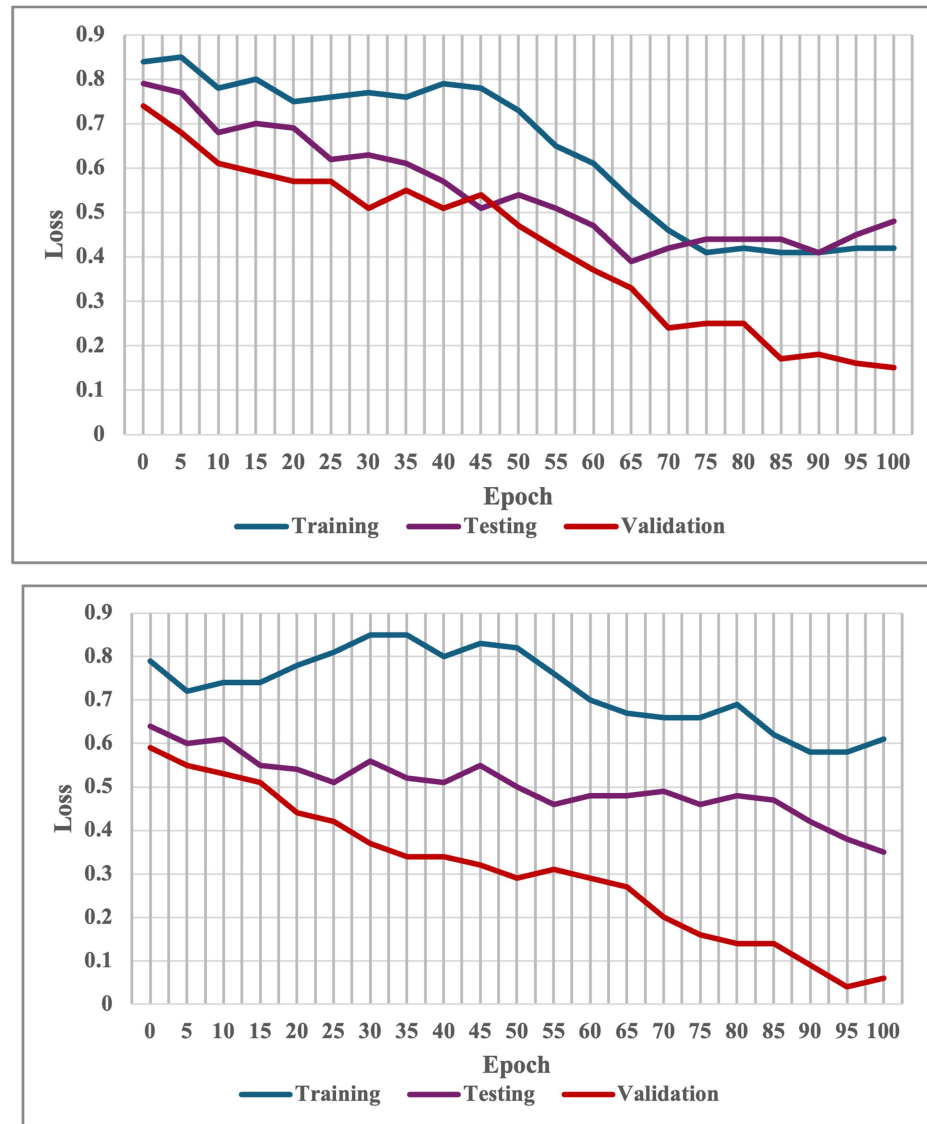


Figure 6: Convergence results (a) VGG-16 (b) ResNet-50 (c) ResNet-101

Figure 6 shows that the data augmentation technique improves the convergence behavior of the machine-learning architectures. As shown in Figure 6(a), the VGG-16 design does not display convergence; the augmentation information of ResNet-50 yields convergence, as in Figure 6(b). ResNet-101 shows comparatively stable convergence among the evaluated machine-learning architectures, as shown in Figure 6(c). The data augmentation process significantly improves ResNet-101 convergence speed.

Among the evaluated models, ResNet-101 with augmented data demonstrated the reported performance characteristics and therefore

represents a potential model for deployment within the proposed system. It always attains optimal recall and improves accuracy and precision with effective convergence capability. The reported data partition of 60:10:30 was used for the evaluated experimental configuration. Such a setup is beneficial as they do not need much information for training. Compared to ResNet-50 and VGG-16, it performs significantly better in execution duration.

CONCLUSION

The study demonstrates the potential of AI-based facial emotion recognition for supporting mental-health monitoring. The AI-ERM model

classified the evaluated emotional categories, including happiness, sadness, and anger, using accuracy, precision, recall, and F-score as performance measures. The AI-ERM using IoT sensors showed effectiveness in the recognition of emotions based on facial expressions that provide considerable data about the psychological state of a person. Use of CNNs enabled the AI-ERM model to learn structured properties in face photos on its own. It significantly improved the detection of subtle facial expressions compared to other traditional ML models (Panda et al., 2024).

The results of the AI-ERM system containing the IoT sensors indicate their application in the therapeutic environment, where constant emotional monitoring is essential in psychological monitoring. The ability to detect and measure feelings in real time gives physicians in-depth insight into patients' psychological differences, allowing immediate solutions. The model could be supplemented with emotion recognition, as with other healthcare tools, such as speech recognition and wearable devices, providing a more comprehensive understanding of patients' psychological and physiological health.

The findings indicate that ML-based emotion recognition integrated with IoT technologies has potential applications in mental-health monitoring by providing a non-invasive and continuous means of assessing emotional states. Facial-expression analysis may support more frequent emotional assessment in clinical settings; however, further clinical validation is required before its use can be associated with improved treatment decisions.

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