An IoT Framework for Emotion Detection and Behavior Influence: Towards Improving the Quality of Life

Nada Asar [1,*], Mohamed Handosa[1], M. Z. Rashad[1]

[1]Department of Computer Science, Faculty of Computers and Information, Mansoura University, Mansoura 35516, Egypt

Emails: Nada.Asar@hotmail.com; Handosa@mans.edu.eg; Magdi z2011@yahoo.com

Abstract

Accurate emotion detection is crucial for individuals facing communication barriers, yet existing approaches struggle with real-time limitations and information Individual privacy. This research presents a new IoT-based framework that integrates EEG and physiological signals from wearable sensors with deep learning models, including CNN, Decision Trees, SVM, KNN, and Naïve Bayes. Unlike traditional methods, our approach effectively mitigates data latency and sensor noise while ensuring compliance with GDPR and HIPAA standards. Experimental results demonstrate a validated accuracy of 99-100%, outperforming state-of-the-art models. These developments establish our framework as a game-changing instrument for affective computing applications, enhancing human-machine interaction and healthcare quality of life.

Keywords: Smart health; Human-machine interaction; Machine learning; Deep learning; Internet of things; Affect Detection; Emotion Detection

1. Introduction

Human contact relies heavily on the ability to recognize and understand emotions. However, expressing emotions is extremely difficult for those with neurocognitive illnesses like Alzheimer's, dementia, ALS, and autism spectrum disorder (ASD). Because these disorders frequently hinder verbal communication, medical personnel and caregivers must rely on subjective indicators such as tone of voice and facial expressions. Unfortunately, there is a knowledge gap about these people's emotional requirements because these conventional approaches are frequently unreliable because of things like social masking or cognitive disability. The world's aging population, which is predicted to make up one-fifth of the global population by 2050, exacerbates this issue. Emotional expression and recognition are made even more difficult by age-related illnesses like dementia and Alzheimer's.

In a similar vein, autism is becoming more and more common; according to recent data, 1 in 44 youngsters has been diagnosed with the disorder. This expanding population calls for innovative methods to accurately recognize and treat emotional states.

A promising approach to overcoming these obstacles is offered by developments in affective computing and Internet of Things (IoT) technology. EEG (electroencephalogram), EDA (electro dermal activity), and EMG (electromyography) are physiological signals that can be recorded using wearable sensors and machine learning algorithms to provide objective information on a person's emotional state[5]. These signals are more trust- worthy for detecting emotions than facial expressions or vocal tones because they are less susceptible to manipulation or cognitive distortion.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

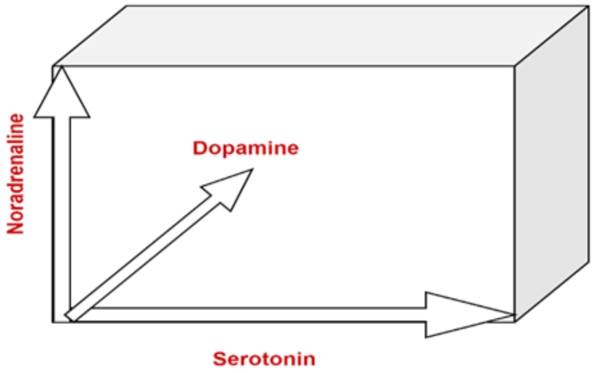


Figure 1. Lovheim's emotions cube [5]

In order to enable precise, ongoing monitoring of emotional states, this study suggests a thorough Internet of Things-based architecture for real-time emotion identification that integrates EEG and other physiological data. The framework achieves high accuracy in emotion categorization by utilizing machine learning classifiers like Decision Trees and SVMs in conjunction with sophisticated deep learning algorithms like CNNs. It also incorporates privacy safeguards to guarantee adherence to GDPR and HIPAA regulations while addressing real-time issues like data latency and sensor noise. This creative method closes the gap in emotion recognition, providing a tool that enhances the quality of life for people with communication difficulties and helps medical professionals and caregivers keep an eye on their emotional health.

2. Related Work

2.1 Wearable IoT Device Integration with Healthcare Frameworks

Because of their sophisticated ability to monitor a wide range of social and medical factors, IoT wearable devices have shown significant promise in the integration of healthcare frameworks. These gadgets, which use deep learning algorithms, have shown promise in offering extremely precise frameworks for enhancing patient quality of life, monitoring the course of diseases, and promoting early intervention. These technologies help caregivers manage patient care more safely and effectively in addition to facilitating the early detection of symptoms. This section reviews previous research efforts that have advanced the field of emotion and affect detection, with a focus on IoT-based solutions.

2.2 Emotion Detection

Previous research, such as that by,[8] introduced a machine learning framework aimed at recognizing emotional states through brain signals, addressing the challenge of signal instability. Techniques like VMD and EMD/IMF were employed to reduce noise and features like Higuchi's fractal dimension (HFD) and entropy were employed for classification, achieving 95.2% accuracy with the DEAP dataset. This study laid groundwork for using EEG in emotion detection but did not address real-time challenges or integration with IoT systems.

Similarly, [9] explored sound-based stimuli and EEG data for emotion identification in people with visual impairments. Using random forest and logistic regression models, the approach achieved 85% and 88% accuracy for positive and negative emotion classification, respectively, but lacked scalability to real-world scenarios.

A ground-breaking method by[10] utilized recurrent neural networks (RNNs) to map brain activity onto visual categories, achieving 83% accuracy. However, this study focused on visual classification rather than direct emotion detection, limiting its application in affective computing.

Several other works in [11][12][13][14][15][16]investigated neural network architectures, including CNNs, LSTMs, and GRUs, achieving high accuracy levels (e.g., 97% with EEG-Brainwave datasets). However, many of these studies relied on small datasets or did not address privacy and latency issues critical to IoT frameworks.

2.3 Affect Detection

In the field of identifying stress and emotions, the use of physiological signals recorded by wearable technology has been extensively explored. Studies like [17] leveraged EDA signals from the Empatica E4 wristband, achieving 85.7% accuracy using random forest models. While effective, these models lacked the ability to process data in real time for continuous monitoring.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

Innovative approaches, such as neural architecture search [18] demonstrated improved performance in binary and three-state classifications of affective states. However, these methods required extensive computational resources, limiting their deployment in IoT applications.

A multimodal framework [19] combined physiological signals with behavioural data, achieving 96.09% accuracy in stress detection. Although robust, this method did not address scalability for large-scale deployment in IoT systems.

Studies targeting autism spectrum disorder (ASD) and behavioural symptoms in dementia [20][21][22][23]provided valuable insights into stress monitoring using wearable sensors. These studies highlighted the importance of customized models but often lacked integration with privacy-preserving measures or edge computing.

2.4 Addressing Gaps in Literature

Our proposed framework builds upon these studies by addressing key limitations such as real-time data processing, privacy compliance, and scalability in IoT-based emotion and affect detection systems. By integrating advanced CNN architectures with robust pre-processing techniques, our approach ensures high accuracy while adhering to GDPR and HIPAA standards and practical applications.

3. Problem Statement

Children with autism spectrum disorder (ASD) and patients with neurological diseases like" Alzheimer's disease, amyotrophic lateral sclerosis (ALS), and dementia" have a difficult time expressing their feelings and coping with day-to-day difficulties. These conditions often impair verbal and non-verbal communication, leading caregivers to rely on subjective cues like facial expressions and vocal tone. However, these methods can be misleading due to social masking or cognitive adaptations, resulting in a lack of accurate emotional understanding.

To address these challenges, leveraging physiological indicators such as electroencephalography (EEG), electro dermal activity (EDA), and electromyography (EMG) offers a more objective and reliable method for emotion classification. These signals are less susceptible to conscious manipulation, making them ideal for intelligent systems, particularly within smart environments (SE). By capturing and analysing these signals in real-time, IoT-enabled devices can provide critical insights into emotional well-being, fostering more effective patient-caregiver interactions. [24] The need for creative solutions is highlighted by the rising need for ambient

-assisted living and context-aware intelligent environments frameworks. IoT-enabled wearables that are inexpensive and non-invasive have a great deal of promise to improve quality of life by detecting emotions and affect in real time. Such technologies can bridge communication gaps, improve emotional monitoring, and support tailored e-health interventions in various medical and residential settings.

3.1 Paper Contribution

Develop Real-Time Emotion detection model within an IoT framework aimed at:

- Proposing an IoT-based Emotion-Affect Detection Framework: A novel architecture designed to classify users' emotional states with high precision.
- Enhancing Feature Selection: Improved techniques for selecting and processing features from raw physiological datasets, ensuring robust and accurate emotion detection.
- Addressing Real-Time Challenges: Implementing strategies to minimize data latency and mitigate sensor noise, enabling reliable real-time performance.
- Ensuring Privacy Compliance: Incorporating privacy-preserving mechanisms aligned with GDPR and HIPAA standards to protect sensitive data.
- Benchmarking Against State-of-the-Art: Providing a detailed comparison with existing methods, demonstrating the framework's superior performance across various metrics.

Section 2 of this study will give a thorough overview of pertinent work, and Section 4 will provide a detailed explanation of the suggested IoT framework. Section 5 will provide the technique and execution specifics, while Section 6 will present the findings and analysis. A summary of the results and suggestions for further research will be included in the paper's conclusion. As seen in Fig. 2, this section presents a thorough IoT-based infrastructure intended to help users make knowledgeable medical decisions through remote monitoring. This idea uses wearable Internet of Things sensors to continuously monitor and assess patients' mental states.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

4. Proposed IoT-Based Framework for Emotion Detection

In this part, as shown in Fig. 2, we introduce a comprehensive IoT-based system intended to help users make medical decisions based on remote monitoring. Wearable Internet of Things sensors are used in this design. To continuously monitor as well as assess patients' mental states

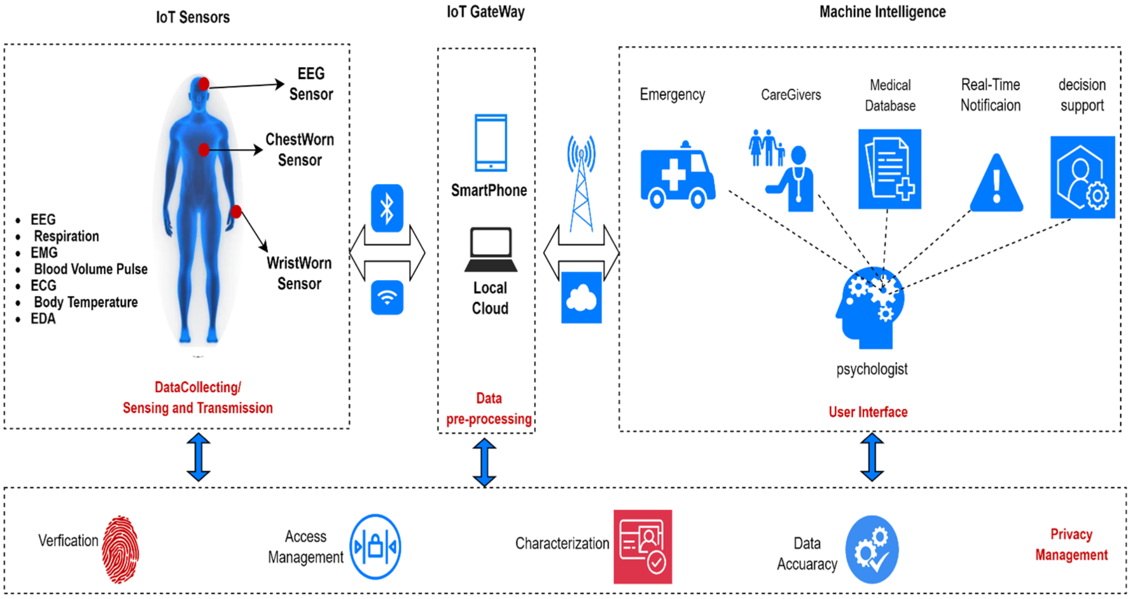


Figure 2. Real-Time IoT Framework for Emotion Detection

4.1 Data Collection, Sensing, and Transmission

The proposed architecture gathers data about users' physiological status using a range of sensors. This includes electroencephalogram (EEG), electromyography (EMG), electrocardiogram (ECG), blood pressure, respiration rate, electro dermal activity (EDA), and body temperature. Additionally, data is collected from smartphones to offer a thorough assessment of the patient's condition. Following that, an IoT gateway receives this data for further processing.

4.2 Pre-processing of Data

Once the information has been collected, the IoT gateway device pre-processes it. This crucial stage entails scaling the data, standardizing it, and removing noise. Our approach prepares the raw dataset for cloud trans-mission using traditional scaling algorithms and one-hot encoding. Furthermore, to extract pertinent features prior to data transfer, the gateway can employ more straightforward feature extraction techniques including statistical analysis and domain-specific algorithms. This dual strategy improves processing speed and reduces bandwidth usage, particularly for real-time applications. Real-time pre-processing of raw data is crucial to guarantee accuracy prior to classification because of the intrinsic limitations of sensors and the possibility of noise interference.

Furthermore, we compute averages of surrounding values for robust analysis in order to mitigate the frequent occurrence of missing values in physiological sensor data.

4.3 User Interface

The IoT health framework's user interface (UI) was designed to meet the various demands of patients, caregivers, and medical professionals. Medical practitioners are adept at managing patient records, analysing past trends, and keeping an eye on patient health data. Caregivers have the ability to communicate with medical specialists, monitor patient health remotely, access graphic data representations, and receive timely notifications. Patients can monitor their development and see their medical records. The UI provides a number of features, such as:

- **Data Visualization**: Sensor data visualization through interactive dashboards.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

- **Alerts and Notifications**: Instant alerts for important occasions.
- **Patient Management**: Resources for safely handling patient data.
- **Communication**: Safe avenues for user involvement.
- **Privacy and Security Settings**: Configure data sharing options and access restrictions.

Overall, the user interface is made to be secure, educational, and easy to use, satisfying the unique needs of every user position and improving the standard of patient care.

4.4 Privacy Management

The suggested IoT-based emotion detection system includes a number of privacy and security measures to guarantee adherence to GDPR and HIPAA:

- **Complete Encryption:** To avoid unwanted access, all physiological data is encrypted during both trans- mission and storage.
- **Multi-Factor Authentication (MFA):** This secure authentication method restricts access to sensitive data to authorized individuals (such as psychologists and caretakers).
- **Data Anonymization:** Privacy risks are reduced by separating physiological data from personally identifiable information (PII).
- **User Control and Consent:** In accordance with the right-to-be-forgotten principle of the GDPR, users have complete control over their data, including the ability to have it deleted.

To further enhance data security, we recommend encrypting and anonymizing sensitive data collected from EEG, respiration, EMG, blood volume pulse, ECG, body temperature, and EDA sensors prior to transmission and storage in the cloud server.

4.5 Handling Sensor Noise and Data Latency

Emotion recognition relies heavily on real-time processing, and we use the following techniques to reduce issues with data latency and sensor noise:

- **Edge Computing:** Edge computing reduces transmission delays by performing crucial calculations (such as feature extraction) locally on smartphones rather than exclusively depending on cloud-based processing.
- **Adaptive Filtering Techniques:** To enhance signal quality, noise reduction techniques like wavelet transformation and Kalman filtering are combined.
- **Latency Benchmarking:** A comparative latency analysis is incorporated to assess performance against current emotion recognition algorithms, and the framework is tuned to attain real-time performance.

5. Materials and Methods

A laptop with 12GB of RAM and an 11th-generation Intel Core ”i7” CPU was used for the trials, along with a Python notebook and a number of open-source libraries. The framework distinctly outlines the steps for collecting and processing data from various sensors, training using a Convolutional- Neural Network algorithm, evaluating results to provide real-time medical decision support, notifications, and comparative analyses.

Our proposed IoT framework consists of two models: the models of emotion detection and affect detection.

5.1 Dataset Description

5.1.1 Emotion-Detection Model

For The Model of Emotion Detection, we employed the dataset [25] developed by Jordon J. Bird—referred to as emotions.csv and available on Kaggle. This dataset was generated using the Muse 2 headband, an IoT smart wearable device equipped with the four electrodes (TP9, TP10, AF7, and AF8) positioned in accordance with the worldwide EEG placement standard of 10–20. The dataset is organized around three emotional states—neutral, positive, and negative—mapped to Lovheim’s emotional model. Specifically, it comprises 2,100 EEG signals distributed as follows:

- Negative: 700 samples (associated with noradrenaline)

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

- Neutral: 695 samples (linked to dopamine)
- Positive: 705 samples (connected to serotonin)

Data were gathered from a male and a female participant. Over a three-minute recording session where they registered their emotional responses.

Dataset Attributes & Limitations:

- Sampling & Balance: Although the class distribution is nearly balanced, the small number of participants may restrict how broadly the results can be applied.
- Sensor Configuration: The use of only four electrodes provides a constrained view of brain activity, which might affect the granularity of emotional state detection.
- Data Quality: Variations in electrode placement and potential motion artifacts can introduce noise, affecting the accuracy of the EEG signals.

5.1.2 Affect Detection Model

The freely available WESAD dataset [26] is used by the Affect Detection Model to identify wearable affect and stress. 15 people's physiological and movement data were gathered for this dataset utilizing devices worn on their wrists and chests. The physiological measurements consist of body temperature, electro-dermal activity, respiration rate, blood volume-pulse, and three-axis acceleration. The dataset employs self-reported metrics from validated questionnaires in addition to sensor data to categorize states into stress, neutral, and amusement; it includes:

Body temperature; three-axis acceleration; respiratory rate; electro dermal activity (EDA); as well as blood volume pulse (BVP) In addition to sensor data, the dataset integrates self-reported measures from established questionnaires to categorize affective states into neutral, stress, and amusement.

Device and Sampling Details:

- RespiBAN Device: records respiration, body temperature, acceleration, ECG, EDA, and EMG at a steady 700 Hz sample rate.
- E4 Empatica: Monitors acceleration, EDA, body temperature, and blood volume-pulse at various rates.

Dataset Attributes & Limitations:

- Multi-modal Data: The combination of physiological signals and self-reported measures enriches the dataset; however, discrepancies between subjective reports and sensor readings may arise.
- Device Variability: Differences in sensor sampling rates and device placements necessitate careful synchronization and may introduce inconsistencies, particularly in real-time applications.
- Participant Diversity: While the inclusion of 15 participants enhances diversity compared to the Emotion Detection Model, variability in sensor attachment and participant movement can still impact data reliability

5.2 Feature Extraction and Model Implementation

We constructed models utilizing deep learning methods in addition to conventional machine learning (ML) classifiers, specifically a Convolutional-Neural Network, to evaluate emotion and affect detection tasks. The next sections provide a detailed description of the CNN architecture's mathematical formulation as well as the feature extraction process.

5.2.1 Emotion-Detection Model

Model Architecture:

Model for Detecting Emotions is implemented within the TensorFlow framework. It processes input EEG signals of shape (2548, 1), representing 2,548-time steps per sample, and outputs a classification into one of three emotional classes: negative, neutral, or positive.

The following are the main elements:

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

Convolution Process each layer applies a series of filters in order to record local temporal data. The convolution operation is stated mathematically as follows:

$$Y[i] = \sum_{j=0}^{N-1} X[i + j] \cdot W[j]$$

For a given input X and a filter W of size N, Each layer applies a group of filters to capture local temporal features.

where *Y [i]* is the *i*th element of the output feature map and N is the filter size.

Activation Function Following convolution, The Rectified Linear Unit (ReLU) activation function is used to introduce non-linearity:

$$\mathrm{f(n) = max(0, n)}$$

CNN Layers structure includes three consecutive CNN layers:

- Layer 1 & Layer 2: Each contains 128 filters.
- Layer 3: Contains 64 filters.

Batch normalization, which aids in stabilizing and speeding up training, and MaxPooling1D operation, which lowers the temporal dimension and prevents overfitting, come right after each convolutional layer.

Layers that are fully connected and Output the feature maps are flattened following the convolutional blocks and passed through a series of dense layers. Dropout layers are interleaved to further reduce overfitting. Three neurons with sigmoid activation characteristics make up the last dense layer.

To output class probabilities for the three emotional states.

Training and Tuning Hyperparameters the Adam optimizer, which dynamically modifies the learning rate during training. The optimizer uses the following ruler to update the model parameters:

$$\theta_t = \theta_{t-1} - \alpha . \frac{v_t}{\sqrt{m_t} + \epsilon}$$

Where:

- Θ_t are the parameters at iteration t,
- m_t represents the estimate of the first moment (mean),
- v_t denotes the estimate of the second moment (variance),
- α refers to the learning rate, and
- € is a small constant added to avoid division by zero.

We used a batch size of 256 and trained the model over 150 epochs. Model Complexity

The model’s total number of trainable parameters is 1,380,707. The model summary is as follows:

Model: "sequential"

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

Layer	Output	Param #
conv1d	(None, 2548, 128)	512
batch normalization	(None, 2548, 128)	512
max_pooling1d	(None, 1274, 128)	0
conv1d_1	(None, 1274, 128)	49280
batch_normalization_1	(None, 1274, 128)	512
max_pooling1d_1	(None, 637, 128)	0
conv1d_2	(None, 637, 64)	24640
max_pooling1d_2	(None, 318, 64)	0
flatten	(None, 20352)	0
dense	(None, 64)	1302592
dropout	(None, 64)	0
dense_1	(None, 32)	2080
dropout_1	(None, 32)	0
dense_2	(None, 16)	528
dropout_2	(None, 16)	0
dense_3	(None, 3)	51

Parameters total: 1380707 (5.27 MB)

Trainable parameters: 5.27 MB, 1380195

Parameters not trainable: 512 (2.00 KB)

5.2.2 Affect Detection Model

The proposed affect detection model employs a CNN tailored for time-series data with a sequence length of 59 time steps and a single feature. The architecture is designed to extract temporal features through a series of convolutional operations, followed by dimensionality reduction and classification. The model structure is summarized below:

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

- **Input Layer**: Accepts sequences of 59 time steps with 1 feature each.
- **Convolutional Layers:**

– Layer 1: A Conv1D layer including 128 filters, "same" padding, a kernel size of 3, and ReLU activation. This layer's output shape is (None, 59, 128).

– Layer 2: Batch Normalization, a MaxPooling1D layer (pool size = 2), a second Conv1D layer with 128 filters, a kernel size of 3, padding set to "same," and ReLU activation, which reduces the output shape to (None, 29, 128).

– Layer 3: A MaxPooling1D layer (pool size = 2) that produces an output shape of (None, 7, 64) comes after a third Conv1D layer with 64 filters, a kernel size of 3, padding set to "same," and ReLU activation.

- **Flattening Layer**: Creates a 448-size vector from the finished feature maps.
- **Dense Layers**: The vector that has been flattened is processed by:

– 64 neurons and tanh activation make up this thick layer.

– A dropout layer with a dropout rate of 0.5 comes after a dense layer with 32 neurons and transactivation.

– A dropout layer with a dropout rate of 0.7 comes after a dense layer with 16 neurons and ReLU activation.

- **Output Layer**: The probabilities for the three emotional classifications are output by the output layer, a dense layer with three neurons, and softmax activation.

The Adam optimizer is used to train the model. For 1000 epochs as well as 500 batch size. It contains 106,851 parameters (with 106,339 trainable and 512 untrainable), and its performance is evaluated on a test set comprising 20% of the overall dataset.

The following is a summary of the model:

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 59, 128)	512
batch_normalization (Batch Normalization)	(None, 59, 128)	512
max_pooling1d	(None, 29, 128)	0
conv1d_2	(None, 29, 128)	49280
batch_normalization_1	(None, 29, 128)	512
max_pooling1d_1 g1D) (MaxPoolin	(None, 14, 128)	0
conv1d_3	(None, 14, 64)	24640
max_pooling1d_2	(None, 7, 64)	0
flatten	(None, 448)	0
dense	(None, 64)	28736
dense_1	(None, 32)	2080

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

dropout	(None,	32)	0
dense_2	(None,	16)	528
dropout_1	(None,	16)	0
dense_3	(None, 3)		51

===

Parameters total: 106851 (417.39 KB)

Trainable parameters: 106339 (415.39 KB)

Parameters not trainable: 512 (2.00 KB)

---

6. Results and Evaluation Analysis

6.1 Emotion Detection Model

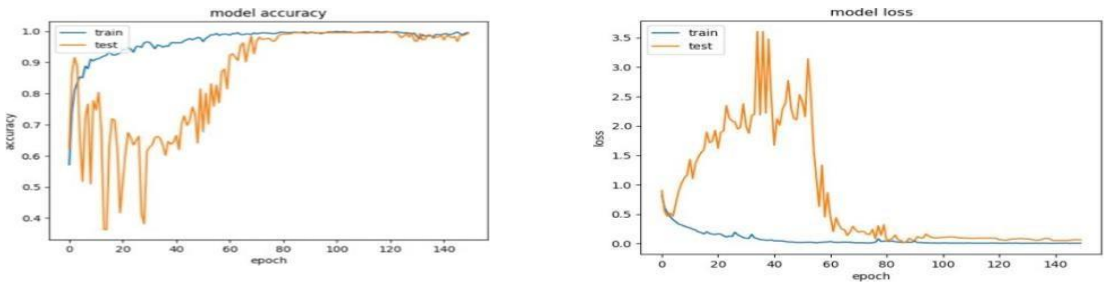
To determine the effectiveness of the proposed CNN model, several traditional machine learning (ML) classifiers were first analyzed as benchmarks. These classifiers included the Support Vector Machine (SVM), Naive Bayes, k-nearest Neighbors (K-NN), Random Forest, and Decision Tree approaches. Each classifier's performance was assessed using the precision, recall, F1-score, and accuracy metrics, as indicated in Table 1.

Table 1 indicates that Random Forest's accuracy was the highest. Among traditional ML classifiers at 97.84%, followed closely by Decision Tree and SVM. In contrast, Naive Bayes performed the worst, with an accuracy of only 65.85%. These findings highlight the need for a more robust approach, such as deep learning, to improve classification performance.

Table 1: Performance Metrics of Various ML Classifiers for Emotion Detection

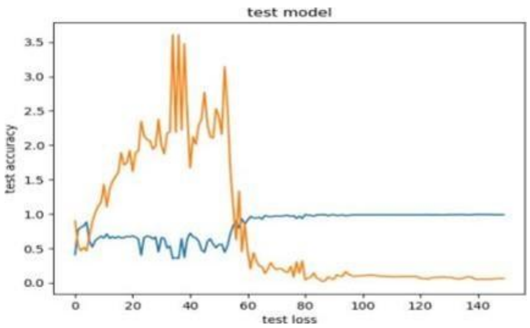
ML Classifier	Precision	Recall	F1-score	Accuracy
SVM	96%	96%	96%	95.96%
Naive Bayes	65%	65%	64%	65.85%
K-NN	95%	95%	95%	94.98%
Random Forest	97.9%	97.8%	97.8%	97.84%
Decision Tree	96.1%	96.1%	96.1%	96.1%

The proposed CNN model was then trained for emotion detection, with the training and testing accuracy curves illustrated in Figure 3. The blue curve represents the training accuracy, which exhibits some fluctuations but ultimately stabilizes at a peak of 99.3% after 150 epochs. Meanwhile, the test accuracy, depicted by the orange curve, shows a consistent upward trend, reaching 99% by the final epoch. The loss curve (Figure 3b) indicates a stable convergence of the model, suggesting minimal overfitting and effective generalization.



(a) Train (b) Loss

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025



(c) Test

Figure 3. Curves of accuracy and loss for the model of emotion detection

Table 2 presents the classification results for human emotion detection, accompanied by evaluation metrics such as precision, recall, and F1-score. The weighted averages for accuracy, recall, and F1-score in this study are consistently 99%, indicating the robust performance of the model across all evaluation criteria.

Table 2: Classification report for the Emotion Detection model

	'precision'	'recall'	'F-measure'	support
Neutral	100%	98%	99%	154
Positive	100%	100%	100%	134
Negative	98%	100%	99%	139
Accuracy	0.99			427
Macro avg	0.99	0.99	0.99	427
Weighted avg	0.99	0.99	0.99	427

6.2 Affect detection model

To ensure high accuracy in affect detection, we utilized both machine learning (ML) and deep learning (DL) algorithms. Various ML classifiers were evaluated, and their performance metrics are summarized in Table 3.

Table 3: ML Classifiers on Affect Detection Model

Classifier	precision	Recall	F-measure	Accuracy
Support Vector-machine	100%	100%	100%	100%
Naive Bayes	100%	100%	100%	100%
KNN	99%	99%	99%	99%
Decision Tree	100%	100%	100%	100%

The CNN model's confusion matrix is shown in Figure 4. Whereas off-diagonal values imply incorrect classifications, diagonal values show occurrences that were correctly classified. , matrix reveals that the model correctly classified 154 neutral, 134 positive and 139 negative instances, reaffirming its high performance across all classes. The near-perfect precision, recall, and F1-score values demonstrate the robustness and reliability of the CNN model in detecting human emotions accurately.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

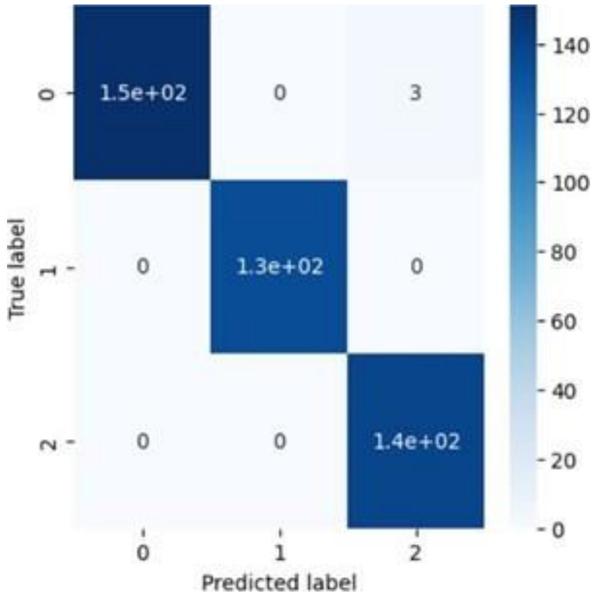
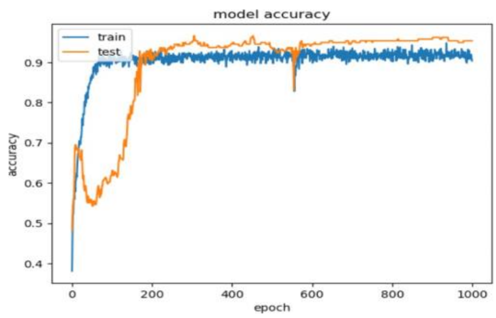


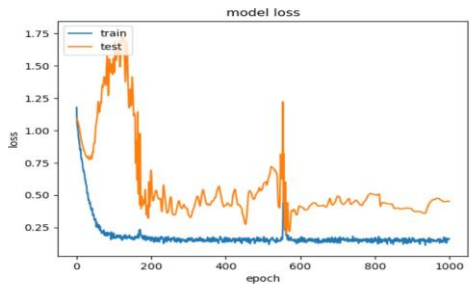
Figure 4. The Emotion Detection model's confusion matrix.

For deep learning, we employed a Convolutional Neural Network (CNN) to analyse multimodal physiological indicators, such as EMG, EDA, respiration, as well as body temperature. This approach enabled consistently high classification accuracy.

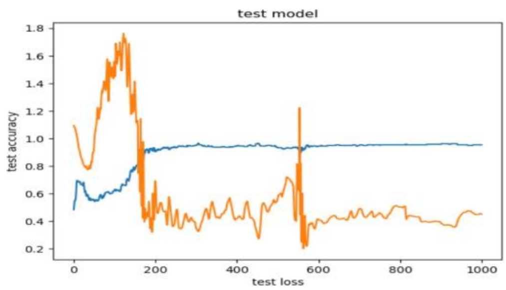
Figure 5 illustrates the training curves, where the cross-entropy loss function and the ADAM optimizer were employed. The blue curve represents training accuracy, which fluctuates before stabilizing at 95.3% after 500 batch sizes throughout 1000 epochs.



(a) Train



(b) Loss



(c) Test

Figure 5. Loss and accuracy curves for the model of affect detection

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

Figure 6 shows the matrix of confusion for the CNN model. The diagonal values indicate correctly classified instances, while misclassifications appear above and below the diagonal. The confusion matrix confirms the presence of 36, 120, and classified instances for stress, amusement, and neutral states, respectively.

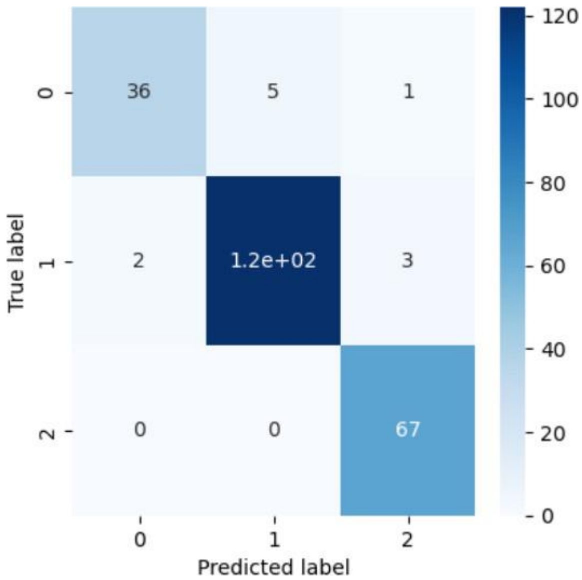


Figure 6. The confusion matrix for the affect detection mode

A comprehensive classification report including precision, recall, and F1-score metrics is shown in Table 4. The model's robustness is demonstrated by the consistent 95% weighted averages for accuracy, recall, and F1-score.

Table 4: Report on classification for the Affect detection model

	Precision	Recall	F1-score	Support
Neutral	0.95	0.86	0.90	42
AMUSEMENT	0.96	0.96	0.96	127
STRESS	0.94	1.00	0.97	67
Accuracy			0.95	236
Macro avg	0.95	0.94	0.94	236
Weighted avg	0.95	0.95	0.95	236

7. Model Evaluation and Discussion

7.1 Emotion Detection model

We employed the Bootstrapping technique to estimate the 95% Confidence Interval (CI) for the accuracy of the emotion detection model. Bootstrapping involves randomly sampling from the test data with replacement and assessing the model on each resampled dataset to compute the accuracy. This process was repeated 150 times to generate a distribution of accuracy scores.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

The resulting 95% Confidence Interval for accuracy was:

(0.9836, 1.0000)

This implies that the model's accuracy is highly stable and reliable.

Additionally, we performed hyperparameter tuning using Keras Tuner to optimize the architecture of the CNN model. The tuning process involved selecting ideal values for several hyperparameters, including kernel size, convolutional layer filter count, dropout rate, and optimizer type. The best-performing hyperparameters are summarized in Table 5.

Table 5: Optimal Hyperparameters for the Emotion Detection Model

Hyperparameter	Optimal Value
Filters (First Conv Layer)	256
Kernel Size (First Conv Layer)	3
Number of Convolutional Layers	2
Filters (Second Conv Layer)	64
Kernel Size (Second Conv Layer)	3
Filters (Third Conv Layer)	256
Kernel Size (Third Conv Layer)	3
Dense Layer Units	64
Activation Function	ReLU
Dropout Rate	0.5
Optimizer	RMSprop

This tuning process identified the optimal configuration for our CNN, enhancing the model's performance.

7.1.1 AUC Calculation and ROC Curve for Multi-Class Classification

To assess the evaluation of the model for emotion detection, we plotted the ROC curve in Figure 7 and calculated the AUC for each class (Neutral, Negative, and Positive).

The test labels (y test) were binarized using label binarize, and the model is predicted probabilities (y pred proba) were used to compute the ROC curve for each class. The FPR and TPR were calculated, and the AUC was determined using the AUC function.

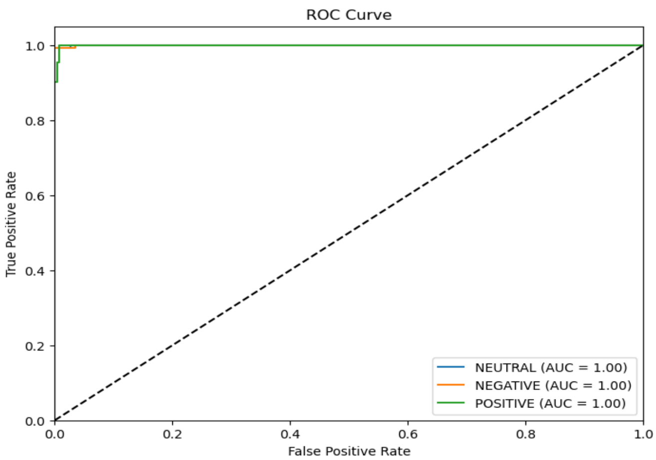


Figure 7. ROC Curve for Emotion Detection Model

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

The AUC for each class was found to be 1, indicating that the model perfectly distinguishes between each class without any errors. An AUC of 1 suggests optimal sensitivity and specificity for each class, making the model highly reliable for emotion detection tasks.

7.2 Affect Detection Model

Bootstrapping for Confidence Interval and Hyperparameter Tuning

The code demonstrates two primary operations: calculating a **95% Confidence Interval (CI)** for model accuracy using **Bootstrapping** and performing **Hyperparameter Tuning** using **Keras Tuner**.

Bootstrapping for Confidence Interval

The first part of the code estimates a **95% Confidence Interval (CI)** using **Bootstrapping** method. Below, this is a breakdown of the process:

Bootstrapping Process:

It performs **resampling with replacement** on the test data (X test, y test) 150 times (n iterations).

For each iteration, the model is evaluated on the resampled data, and the accuracy score is appended to the accuracy scores list.

Finally, the **2.5th** and **97.5th** percentiles of the accuracy scores are calculated to determine the 95% CI.

The resulting output was:

95% Confidence Interval for Accuracy: (0.9237, 0.9746)

This indicates that the model's true accuracy lies between 0.9237 and 0.9746 with 95% confidence.

Hyperparameter Tuning using Keras Tuner

The second part of the code uses **Keras Tuner** to perform **Random Search** for hyperparameter optimization in a CNN. The key elements are as follows:

Model Building with Hyperparameters:

The buildmodelfunction defines a CNN with a variable number of layers, filters, kernel sizes, dense units, and dropout rates.

The optimizer, loss function, and activation functions are also selected based on the hyperparameter

Random Search:

kt.RandomSearchis used to search the hyperparameter space. It tries different combinations (maxtrials=5) to find the best configuration based on **validation accuracy**.

Best Hyperparameters:

After the search is completed, the best hyperparameters are retrieved and printed:

Reloading Tuner from .\untitledproject\tuner0.json

{'filters': 256, 'kernelsize': 3, 'numlayers': 2, 'filters0':

64, 'kernelsize0': 3, 'denseunits': 64, 'activation': 'relu',

'dropoutrate': 0.5, 'optimizer': 'rmsprop', 'filters1': 256, 'kernelsize1':3, 'filters2': 256, 'kernelsize2': 3}

These hyperparameters represent the optimal configuration for the model, suggesting:

- The model should have **256 filters** in the first and third convolutional layers, and **64 filters** in the second layer.
- The **kernel size** for all layers should be **3**.
- The model should consist of **2 convolutional layers** and use 0.5 dropout rate .
- Optimizer should be **RMSprop**, and the activation function should be **ReLU**.
- **Hyperparameter Tuning** using **Keras Tuner** has led to the optimal model configuration, im- proving model performance by finding the best combination of hyperparameters.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

ROC and AUC Curve for Affect Detection-Model

Affect detection model's evaluation is completed. Using the ROC curve as well as AUC, to assess how well it performed in distinguishing between different emotional states.

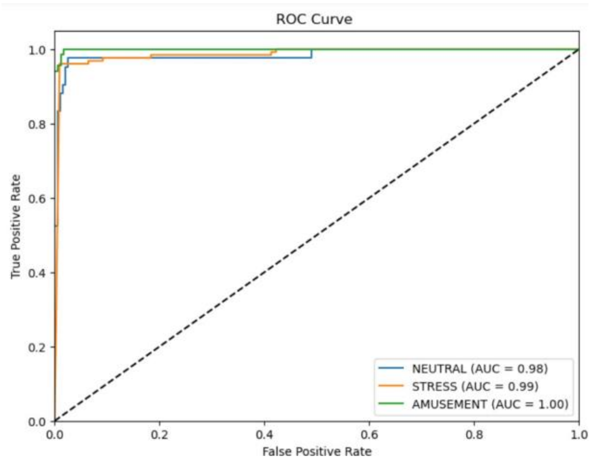


Figure 8. ROC Curve for Affect Detection Model

AUC Results

The AUC values for the model are:

- **Neutral Class:** = 0.98
- **Stress Class:** = 0.99
- **Amusement Class:** = 1.00

The model demonstrates excellent performance across all affect states:

- **Neutral**: AUC of 0.98 indicates strong classification accuracy.
- **Stress**: AUC of 0.99 shows robust ability to distinguish Stress from other emotions.
- **Amusement**: AUC of 1.00 suggests perfect identification of this emotional state.

8. Comparing of our suggested model with current methods

This section offers a comparison of the suggested model against established approaches in the field. Our goal is to emphasize the advantages and limitations of research methodology relative to existing models. The results demonstrate that our approach not only enhances classification performance but also offers greater robustness in emotion detection, thereby contributing significantly to the advancement of this domain.

Table 6: Comparison between our proposed model for emotion detection and existing approaches

Study	Year	Dataset	Algorithm Used	Accuracy
Mridha, Krishna, et al.[27]	2023	Brainwave	DNN, LSTM, GRU	98.44%, 97.5%, 97.18%
Thakur, Er Shrawan[28]	2023	Brainwave	RF, Na¨ıve-Bayes, R- NN, LSTM, Neural Network	96.03%, 94.72%, 82.45%, 84.05%, 80.68%

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

d Momenul Haque, M., et al.[29]	2023	Brainwave	LSTM-GNB, LSTM-SVM, LSTM-LR and LSTM-DT	95%, 65%, 96%, 97%, 96%
Jha, S.K., Suvvari, S. & Kumar, M[30]	2024	Brainwave DEAP	CNN	98.10%, 81%
Abgeena, Abgeena, and Shruti Garg.[31]	2023	SEED, Brainwave	S-LSTM-ATT	97.83%, 98.36%
Proposed Study	2024	Brainwave	CNN, SVM, Na¨ıve-Bayes, K-NN, RF, DT	99%, 96%, 65.85%, 94.98%, 96.1%

Table 7: Comparison between our proposed model for affect detection and existing approaches

Study	Year	Dataset	Algorithm Used	Accuracy
Malviya, L. et al.[32]	2023	WESAD	LSTM	98%
Almadhor, Ahmad, et al.[33]	2023	WESAD	DNN	86.82%
Singh, Ghanapriya, Orchid Chetia Phukan, and Ravinder Kumar[34]	2023	WESAD	CNN-LSTM	91.52%
Jizhong Liu, Mengqian Li, Chaozhu He, Tianshu Fang, and Mingxu Feng[35	2024	WESAD	LSTM-1DCNN Binary classification	87.82%, 94.9%
Singh, Ghanapriya, et al.[36]	2024	WESAD	CNN-LSTM	90.45%
Proposed Study	2024	WESAD	CNN, SVM, Naive Bayes, K-NN, Deci- sion Tree	95.3%, 100%, 100%, 99%, 100%

9. Conclusion and Future Research Efforts

Wearable biosensors are poised to revolutionize the detection of human emotions, with substantial implications for mental well-being management. This study demonstrated the efficacy of lightweight IoT-based biomedical sensors in accurately inferring emotional states, achieving a remarkable accuracy rate of 99% using our emotion-affective state mining methodology. The convolutional neural networks (CNNs) employed were crucial in extracting deep features, which were essential for this high level of accuracy.

The implementation of our prototype validated the practicality of the IoT framework for real-time emotion detection, displaying its potential for use in various applications. Several machine learning classifiers, some of which achieved

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

up to 100% accuracy, were also utilized. While the deep CNN-based approach notably enhanced the performance, there is stillroom for improvements using alternative methodologies.

The IoT framework includes robust privacy mechanisms that allow for the safe collection and analysis of sensitive data, essential for early detection of mental health conditions, leading to improved patient outcomes. Through improved communication techniques, a deeper comprehension of user emotions, and an increase in user satisfaction overall, this novel method has the capacity to transform the domains of psychology as well as human-computer interaction.

Even if the results are encouraging, ensemble models—like the one that has been suggested—are computationally demanding and take a lot of time and money to train. Further studies should focus on developing robust and effective models that can achieve high accuracy with fewer training parameters.

To sum up, this study presents a novel method for detecting emotions that has broad applications in many different fields. We think that our results will stimulate more investigation and creativity in this exciting area.

10. Future Research

Future studies should concentrate on improving real-time performance by:

- Tackling issues like sensor noise and data latency, building on the current findings.
- Investigating additional datasets in order to improve the model's generalization over a range of states.
- Improving computational efficiency to cut down on training time and model complexity.
- Verifying the benefits of the suggested framework by contrasting it with the most advanced emotion detection models.

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest."

References

[1] United Nations, Department of Economic and Social Affairs, Population Division, *World Population Ageing: 2017 Highlights.* UN, 2017. Available: https://www.un.org/development/desa/pd/sites/ www.un.org. development.desa.pd/files/files/documents/2017/Feb/un_pop_ageing_2017.pdf

[2] T. M. Rutkowski, M. S. Abe, M. Koculak, and M. Otake-Matsuura, "Classifying mild cognitive impairment from behavioral responses in emotional arousal and valence evaluation task–AI approach for early dementia biomarker in aging societies," in *Proc. 42nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2020, pp. 5537–5543. DOI: 10.1109/EMBC44109.2020.9176110

[3] C. Lord and S. L. Bishop, "Recent advances in autism research as reflected in DSM-5 criteria for autism spectrum disorder," *Annu. Rev. Clin. Psychol.*, vol. 11, pp. 53–70, 2015. DOI: 10.1146/annurev-clinpsy-032814-112955

[4] S. Ji et al., "Emotion recognition of autistic children based on EEG signals," in *Int. Conf. Comput. Eng. Netw*, 2022, pp. 698–706. DOI: 10.1007/978-3-030-87311-5_73

[5] H. Lövheim, "A new three-dimensional model for emotions and monoamine neurotransmitters," *Med. Hypotheses*, vol. 78, no. 2, pp. 341–348, 2012. DOI: 10.1016/j.mehy.2011.11.020

[6] Ž. Stržinar et al., "Stress detection using frequency spectrum analysis of wrist-measured electrodermal activity," *Sensors*, vol. 23, no. 2, p. 963, 2023. DOI: 10.3390/s23020963

[7] R. Tanwar, O. C. Phukan, G. Singh, and S. Tiwari, "CNN-LSTM based stress recognition using wearables," *IEEE Access*, 2022. DOI: 10.1109/ACCESS.2022.3157630

[8] R. Alhalaseh and S. Alasasfeh, "Machine-learning-based emotion recognition system using EEG signals," *Computers*, vol. 9, no. 4, p. 95, 2020. DOI: 10.3390/computers9040095

[9] J. L. López-Hernández et al., "Framework for the classification of emotions in people with visual disabilities through brain signals," *Front. Neuroinformatics*, vol. 15, p. 642766, 2021. DOI: 10.3389/fninf.2021.642766

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

[10] C. Spampinato et al., "Deep learning human mind for automated visual classification," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 6809–6817. DOI: 10.1109/CVPR.2017.726

[11] G. Cao et al., "Emotion recognition based on CNN," in *Proc. Chinese Control Conf. (CCC)*, 2019, pp. 8627–8630. DOI: 10.1109/CCC.2019.8866555

[12] S. Mohsen and A. G. Alharbi, "EEG-based human emotion prediction using an LSTM model," in *Proc. IEEE Midwest Symp. Circuits Syst. (MWSCAS)*, 2021, pp. 458–461. DOI: 10.1109/MWSCAS51074.2021.9423768

[13] M. K. Chowdary, J. Anitha, and D. J. Hemanth, "Emotion recognition from EEG signals using recurrent neural networks," *Electronics*, vol. 11, no. 15, p. 2387, 2022. DOI: 10.3390/electronics11152387

[14] K. M. S. Bano, P. Bhuyan, and A. Ray, "EEG-based brain-computer interface for emotion recognition," in *Proc. Int. Conf. Comput. Intell. Netw. (CINE)*, 2022, pp. 1–6. DOI: 10.1109/CINE53271.2022.9935323

[15] N. S. Suhaimi, J. Mountstephens, and J. Teo, "A dataset for emotion recognition using virtual reality and EEG (DER-VREEG): Emotional state classification using low-cost wearable VR-EEG headsets," *Big Data Cogn. Comput.*, vol. 6, no. 1, p. 16, 2022. DOI: 10.3390/bdcc6010016

[16] C. L. Kwan et al., "Wearable technology for detecting significant moments in individuals with dementia," *BioMed Res. Int.*, vol. 2019, 2019. DOI: 10.1155/2019/3574051

[17] L. Zhu et al., "Feasibility study of stress detection with machine learning through EDA from wearable devices," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2022, pp. 4800–4805. DOI: 10.1109/ICC45855.2022.9837249

[18] L. Huynh et al., "StressNAS: Affect state and stress detection using neural architecture search," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput. Wearable Comput.*, 2021, pp. 121–125. DOI: 10.1145/3460418.3482805

[19] R. Walambe et al., "Employing multimodal machine learning for stress detection," *J. Healthc. Eng.*, vol. 2021, pp. 1–12, 2021. DOI: 10.1155/2021/6632475

[20] A. Iaboni et al., "Wearable multimodal sensors for the detection of behavioral and psychological symptoms of dementia using personalized machine learning models," *Alzheimer's Dementia: Diagn. Assess. Dis. Monit.*, vol. 14, no. 1, p. e12305, 2022. DOI: 10.1002/dad2.12305

[21] M. T. Tomczak et al., "Stress monitoring system for individuals with autism spectrum disorders," *IEEE Access*, vol. 8, pp. 228236–228244, 2020. DOI: 10.1109/ACCESS.2020.2994573

[22] A. G. Airij, R. Bakhteri, and M. Khalil-Hani, "Smart wearable stress monitoring device for autistic children," *J. Teknologi*, vol. 78, no. 7–5, 2016. DOI: 10.11113/jt.v78.9342

[23] J. Li et al., "APEN: A stress-aware pen for children with autism spectrum disorder," in *Int. Work-Conf. Interplay Natural Artif. Comput.*, 2022, pp. 281–290. DOI: 10.1007/978-3-030-86052-8_27

[24] D. Monekosso, F. Florez-Revuelta, and P. Remagnino, "Ambient assisted living [guest editors' introduction]," *IEEE Intell. Syst.*, vol. 30, no. 4, pp. 2–6, 2015. DOI: 10.1109/MIS.2015.65

[25] J. J. Bird, A. Ekart, C. D. Buckingham, and D. R. Faria, "Mental emotional sentiment classification with an EEG-based brain-machine interface," in *Proc. Int. Conf. Digital Image Signal Process. (DISP'19)*, 2019. DOI: 10.1109/DISP.2019.10004

[26] P. Schmidt et al., "Introducing WESAD, a multimodal dataset for wearable stress and affect detection," in *Proc. 20th ACM Int. Conf. Multimodal Interact.*, 2018, pp. 400–408. DOI: 10.1145/3242969.3242987

[27] K. Mridha et al., "Emotion recognition: A new tool for healthcare using deep learning algorithms," in *Int. Conf. Electr. Electron. Eng.*, 2023, pp. 613–631. Springer.

[28] E. S. Thakur, "Treatment of imbalance dataset for human emotion classification," *World J. Neurosci.*, vol. 13, no. 4, pp. 173–191, 2023.

[29] M. M. Haque et al., "EEG-based multi-class emotion recognition using hybrid LSTM approach," *Int. J. Innov. Res. Comput. Sci. Technol.*, vol. 11, no. 3, pp. 1–6, 2023.

DOI: https://doi.org/10.54216/FPA.190113
Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025

[30] S. K. Jha, S. Suvvari, and M. Kumar, "Emotion recognition from electroencephalogram (EEG) signals using a multiple column convolutional neural network model," *SN Comput. Sci.*, vol. 5, no. 2, pp. 1–14, 2024.

[31] A. Abgeena and S. Garg, "S-LSTM-ATT: A hybrid deep learning approach with optimized features for emotion recognition in electroencephalogram," *Health Inf. Sci. Syst.*, vol. 11, no. 1, p. 40, 2023.

[32] L. Malviya et al., "Mental stress level detection using LSTM for WESAD dataset," in *Proc. Data Anal. Manage ICDAM 2022*, 2023, pp. 243–250. Springer.

[33] A. Almadhor et al., "Wrist-based electrodermal activity monitoring for stress detection using federated learning," *Sensors*, vol. 23, no. 8, p. 3984, 2023. DOI: 10.3390/s23083984

[34] G. Singh, O. C. Phukan, and R. Kumar, "Stress recognition with multi-modal sensing using bootstrapped ensemble deep learning model," *Expert Syst.*, vol. 40, no. 6, p. e13239, 2023.

[35] M. Feng et al., "Affect and stress detection based on feature fusion of LSTM and 1D CNN," *Comput. Methods Biomech. Biomed. Eng.*, vol. 27, no. 4, pp. 512–520, 2024.

[36] G. Singh, O. C. Phukan, R. Gupta, and A. Nayyar, "Hybrid deep learning model for wearable sensor-based stress recognition for Internet of Medical Things (IoMT) system," *Int. J. Commun. Syst.*, vol. 37, no. 3, p. e5657, 2024. DOI: 10.1002/csy.5657

[37] F. Khan, "Deep learning for natural language processing," *J. Deep Learn. Genomic Data Anal.*, vol. 2, no. 2, pp. 1–11, 2022.

DOI: https://doi.org/10.54216/FPA.190113

Received: October 18, 2024 Revised: January 13, 2025 Accepted: February 07, 2025