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NeuroEmotionNet: A lightweight and interpretable 1D CNN Framework for Real-Time EEG Emotion Classification

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Abstract

Mental health disorders, including anxiety, depression, and emotional dysregulation, affect hundreds of millions globally, yet early diagnosis remains a challenge due to the reliance on subjective assessments such as psychometric tests and clinician observations. While EEG-based emotion recognition offers a non-invasive, cost-effective alternative, existing approaches are limited by small and imbalanced datasets, handcrafted features, and lack of real-time deployability. These gaps hinder the development of scalable and clinically relevant emotion detection systems. To address these limitations, this study proposes a machine learning framework for real-time, accurate emotional state classification using EEG signal analysis. The dataset comprises EEG recordings from 300 participants (158 male, 142 female), labeled across four emotional states: Positive, Neutral, Anxiety, and Depression. Signals were collected using an 8-channel EEG device and decomposed into frequency bands (alpha, beta, gamma) using Discrete Wavelet Transform (DWT), with Shannon Entropy applied for complexity analysis. Data augmentation techniques—Generative Adversarial Networks (GAN), SMOTE, and ADASYN—were used to generate 20,000 synthetic instances per method, addressing class imbalance and data scarcity. A comparative evaluation was conducted across nine classical and deep learning models, including Support Vector Machine, Decision Tree, Random Forest, and a 1D Convolutional Neural Network (NeuroEmotionNet). The models were assessed using accuracy, precision, recall, F1-Score, Matthews Correlation Coefficient (MCC), and PR AUC, with latency tracked for real-time viability. NeuroEmotionNet achieved the highest performance with an F1-Score of 98.16%, MCC of 98.2%, and inference time under 3.2 milliseconds on the combined augmented dataset. The novelty of this study lies in its integration of hybrid feature extraction, multi-strategy augmentation, and real-time deployment. A fully functional web application was developed, making this the only study among comparable works to achieve both high accuracy and practical applicability. This research paves the way for scalable, interpretable, and real-time emotion monitoring systems in mental healthcare environments.

Keywords: Electroencephalogram; 1D CNN; DWT; Mental Health Monitoring; ADASYN; Deep Learning

1. Introduction

Mental health disorders, such as depression, anxiety, and emotional instability, rank among the leading causes of disability globally, impacting more than 970 million individuals as of 2022, according to the World Health Organization (WHO). Depression alone affects over 280 million people, while anxiety disorders affect around 301 million. Together, these conditions contribute to a global economic burden exceeding USD 1 trillion each year due to decreased productivity and increased healthcare costs.

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Despite their widespread prevalence, diagnosing emotional disorders primarily relies on subjective tools, including psychometric interviews, behavioral observations, and rating scales. These traditional methods can be influenced by observer bias, are constrained by time, and often lack scalability, making early detection and objective monitoring difficult.

Electroencephalography (EEG) presents a non-invasive and cost-effective solution by recording neural activity with millisecond-level temporal resolution. EEG signals consist of several frequency bands—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–150 Hz)—that correspond to various emotional and cognitive states. For example, alpha and beta activity is associated with relaxation and alertness, while gamma waves relate to arousal and higher-order cognitive functions. However, EEG signals are high-dimensional, non-linear, and sensitive to noise, which requires advanced feature extraction and learning techniques to achieve accurate emotional classification.

Although there has been progress in using machine learning (ML) and deep learning (DL) for EEG-based emotion recognition, several limitations remain. First, many studies use limited and imbalanced datasets, which affect model generalization and introduce classification bias, especially in multi-class emotion prediction. Second, reliance on handcrafted statistical features fails to capture the complex dynamics of EEG signals, leading to underfitting and reduced performance. Third, a lack of comprehensive comparisons among various ML and DL algorithms limits understanding of model robustness in different data conditions. Additionally, generative augmentation methods, particularly Generative Adversarial Networks (GANs), are underused, resulting in insufficient data diversity and poor class imbalance management. Finally, many frameworks do not consider latency-aware evaluation, which is crucial for real-time applications in clinical settings where computational efficiency and predictive accuracy are essential.

This study aims to develop a machine learning framework for the real-time, accurate, and interpretable classification of emotional states through EEG signal analysis. The primary objectives of this study are (1) Develop a robust system that combines traditional machine learning models with 1D convolutional neural networks (CNN) to effectively detect four emotional states from EEG signals. (2) Utilize Discrete Wavelet Transform (DWT) and Shannon Entropy to extract meaningful frequency-domain and complexity features from multiband EEG signals. (3) Address data scarcity and imbalance by generating synthetic samples, enabling balanced and diverse training across emotion classes. (4) Ensure transparency and trust by selecting models that are low-latency and interpretable, making them suitable for practical integration into mental healthcare support systems.

To achieve these goals, this study introduces a system for recognizing emotional states using brain signals, utilizing real patient data augmented with advanced methods to overcome data limitations. It evaluates various machine learning models for accuracy and speed on balanced, diverse datasets (Figure 1). The findings reveal that Decision Tree and Multi-Layer Perceptron (MLP) models perform particularly well, making them suitable for real-time mental health monitoring. This work marks a significant step forward in developing practical emotion detection systems in healthcare. The key contributions of this study are as follows:

- Presented a clinically relevant EEG dataset comprising 300 subjects, labeled across four emotional states: Positive, Neutral, Anxiety, and Depression. This dataset is enriched with gender and age information, allowing for personalized modeling.
- Proposed a robust feature extraction pipeline that utilizes Discrete Wavelet Transform (DWT) and Shannon Entropy that captures frequency-specific characteristics and signal complexity across EEG channels.
- Addressed challenges related to class imbalance and small sample sizes by applying synthetic data generation techniques, including Generative Adversarial Networks (GANs), SMOTE (Synthetic Minority Over-sampling Technique), and ADASYN (Adaptive Synthetic Sampling).
- Conducted a comprehensive comparison of nine machine learning and deep learning classifiers, identifying Decision Tree and Multi-Layer Perceptron (MLP) as the most effective models. These models achieve 100% accuracy with ultra-low latency, ranging from 0.6 to 3.2 milliseconds.
- Demonstrated that integrating data augmentation with model diversity enables the development of a scalable, explainable, and real-time emotion recognition system using EEG. This advancement opens up opportunities for practical deployment in intelligent mental healthcare systems.

The rest of the paper is structured as follows: Section 2 presents related works on plant disease detection and highlights existing limitations. Section 3 describes the datasets, preprocessing techniques, and model architecture. Section 4 reports experimental results, including evaluation metrics and comparisons with state-of-the-art methods. Section 5 discusses findings, practical implications, and limitations. Finally, Section 6 concludes the paper and outlines future directions for research and deployment.

2. Related Work

The scientific community found that EEG signals can capture the activities in the human brain [1]. Therefore, EEG has been used to analyze brain activities, functions, and states, e.g., emotional states [2] [3]. It is widely accepted from psychological theory that human emotions can be classified into six archetypal emotions: surprise, fear, disgust, anger, happiness, and sadness. Humans have more complex emotional cues, which are not easily observable. Facial motion, the tone of the speech, body language, and their complex combinations play a significant role in expressing these emotions. Humans can recognize these complex forms of emotions by processing information acquired by their visual and auditory systems. One of the challenges an EEG-based emotion recognition system faces is differentiating between these emotion categories because every individual's expression of emotion is different depending on the stimuli [4].

EEG data is rapidly being used to train artificial intelligence systems, notably machine learning (ML) and deep learning (DL) algorithms. As a result, significant preprocessing is frequently necessary to eliminate artifacts [5], mainly when EEG data is recorded simultaneously. EEG has several limitations that impair analysis and processing performance, including a weak signal-to-noise ratio [6], nonlinearity, and nonstationary features [7].

Various works have been done using the Database for Emotion Analysis using Physiological signals (DEAP), which is used for emotion analysis using EEG, physiological, and video signals, to compare performance on emotion recognition tasks. The Emotion Recognition Task assesses the ability to recognize six fundamental emotions in a spectrum of facial expression intensity.

Bazgir et al. [8] developed a detection system following the valence/arousal model, leveraging EEG signals, which were initially subjected to decomposition into gamma, beta, alpha, and theta frequency bands via discrete wavelet transform (DWT), then spectral features were extracted from each of these frequency bands. A dimensionality-preserving transformation was employed using Principal Component Analysis (PCA). They used a cross-validated Support Vector Machine (SVM) with radial basis function (RBF-SVM) kernel using extracted features of 10 EEG channels on the DEAP dataset, achieving 91.1% valence and 91.3% arousal accuracy both within the beta frequency band.

Balan et al. [9] employed a range of ML and DL models, SVM, k-Nearest Neighbors (kNN), Random Forest Classifier (RF), and Linear Discriminant Analysis (LDA) and experimented using both with and without feature selection. They recognized and classified fear levels using data from the DEAP dataset, where they characterized fear by low valence, high arousal, and low dominance. They proposed two paradigms for estimating fear level, where RF achieved the highest F scores of 89.96% and 85.33% for the two paradigms, respectively.

Nawaz et al. [10] wanted to pinpoint the most discriminating features for identifying emotions by employing a three-dimensional model of emotion to discern emotions evoked by music videos. The dataset was collected by making the participants watch one-minute videos while their EEG activity was recorded. They extracted power, entropy, fractal dimension, statistical characteristics, and wavelet energy, then compared the Relief based algorithm and PCA and validated the efficacy of the features using SVM, Decision Tree (DT) classifiers, and kNN, with an overall highest classification accuracy of 77.62% for valence, 78.96% for arousal, and 77.60% for dominance.

Doma and Pirouz [11] analyzed the epoch data from the EEG channels both with and without PCA for dimensionality reduction. They utilized Grid search for hyper-parameter optimization to reduce execution times, and compared using SVM, kNN, LDA, Logistic Regression, and DT in the DEAP Dataset. The combination of PCA with SVM exhibited the highest performance, an F1-score of 84.73% and a recall rate of 98.01% [12], [13].

Ullah et al. [14] proposed a pyramidal one-dimensional convolutional neural network (P-1D-CNN) with 61% fewer parameters than standard CNN models. Using the University of Bonn dataset, P-1D-CNN achieved an accuracy of 99.1%, with a minimal deviation of 0.9%, within an extremely short detection time of less than 0.000481 seconds.

Chakraborty and Mitra [15] proposed a variational mode decomposition (VMD) method, and introduced a novel approach based on kurtosis to automatically select the critical parameters, K and α, for the VMD decomposition of EEG signals. They applied this to the Bonn University dataset, which after extracting features by bandwidth and spectral features, achieved 98.7% accuracy using an RF classifier.

3. Methodology

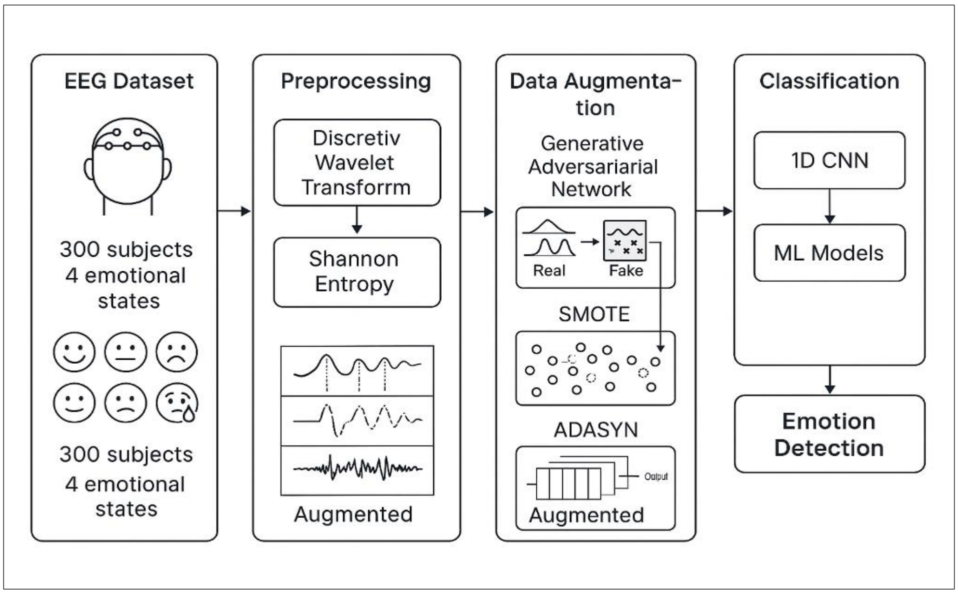

Figure 1 Proposed methodology

3.1. Data Description

This study utilizes an EEG dataset collected from 300 individuals (158 male, 142 female), aged between 15 and 60 years, to classify four emotional states: Positive, Neutral, Anxiety, and Depression [16], [17]. The EEG signals were acquired using an 8-channel EEG machine with electrodes strategically placed on the frontal, parietal, and occipital regions of the scalp, capturing frequency information associated with alpha, beta, and gamma bands. Each participant was evaluated in an eye-open resting state to ensure consistency in cognitive activation, eliminating delta and theta bands typically prominent during sleep or drowsiness. The dataset comprises eight input features: gender, age, and six EEG frequency band metrics—low alpha (8–10 Hz), high alpha (10–13 Hz), low beta (13–17 Hz), high beta (17–30 Hz), low gamma (30–50 Hz), and high gamma (50–100 Hz). The target variable denotes the emotional state category of the individual. Table 1 presents the class distribution, highlighting a degree of imbalance across emotional categories. To address this, three data augmentation techniques—Generative Adversarial Networks (GANs), Synthetic Minority Over-sampling Technique (SMOTE), and Adaptive Synthetic Sampling (ADASYN)—were applied, generating up to 20,000 synthetic instances per method [18], [19]. These synthetic datasets were statistically validated using mean, variance, and standard deviation analyses, confirming their close approximation to the original data distributions. Ethical approval was obtained prior to data collection, and all participants or their guardians provided informed consent. Personally identifiable information was anonymized to preserve privacy in accordance with institutional review board (IRB) protocols.

Table 1 Patient Demographics and Emotional State Distribution

Gender	Count	Age Range (years)	Positive	Neutral	Anxiety	Depression
Male	158	15–60	24	50	46	38
Female	142	15–59	44	35	28	35
Total	300	15–60	68	85	74	73

3.2. Data Preprocessing

Raw EEG signals are inherently noisy and susceptible to various artifacts, including those caused by eye movement, facial muscle contractions, and ambient electrical interference. To mitigate these effects, a band-pass filter was applied to retain only the alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz) frequency bands. Delta and theta bands, typically associated with sleep and low-arousal states, were excluded due to the eye-open, alert-state nature of the recordings. During the EEG acquisition process, participants were instructed to sit still, avoid blinking, and maintain a neutral facial expression to reduce motion-induced signal contamination. Following artifact removal, normalization was applied to the numerical EEG features using min-max scaling, ensuring that all values were rescaled to a range between 0 and 1. This step helped eliminate bias caused by feature magnitude disparities and improved model convergence during training. In parallel, statistical analysis was conducted to detect outliers or corrupted samples. Any entries with missing values or significant deviations due to faulty sensor readings were discarded to maintain dataset integrity. Categorical attributes such as gender were one-hot encoded to facilitate compatibility with machine learning classifiers without introducing implicit ordinal relationships [20]. The target variable, denoting the emotional state, was label-encoded into four classes: Positive (0), Neutral (1), Anxiety (2), and Depression (3), enabling multi-class classification across the pipeline. To ensure consistent evaluation, the dataset was partitioned into training (70%), validation (15%), and test (15%) sets using stratified sampling.

3.3. Data Augmentation

Due to the limited size (300 samples) and class imbalance in the original EEG dataset, data augmentation was employed to enhance model generalization and improve performance, especially for underrepresented emotional states. Three techniques were utilized: Generative Adversarial Networks (GAN), Synthetic Minority Over-sampling Technique (SMOTE), and Adaptive Synthetic Sampling (ADASYN). GANs generated entirely new samples by learning the underlying data distribution through an adversarial training process between a generator and a discriminator. This approach introduced high-diversity synthetic data, reducing overfitting while maintaining signal complexity. In contrast, SMOTE created synthetic samples by interpolating between minority class samples and their nearest neighbors, preserving local data structure [21]. ADASYN extended SMOTE by focusing on more difficult-to-learn instances, adaptively generating samples based on the density of minority classes. Each method contributed 20,000 new instances, resulting in five datasets: the original, original + GAN, original + SMOTE, original + ADASYN, and a combined dataset using all three techniques. Statistical measures—mean, variance, and standard deviation—were computed for all EEG features to validate the synthetic data. The distributions closely matched the original dataset, confirming the reliability and consistency of the generated samples. Together, these augmentation strategies significantly increased dataset diversity and balance, enabling more robust training of both classical and deep learning models in emotional state classification tasks.

3.4. Feature Extraction

Effective feature extraction is critical for analyzing EEG signals, which are inherently non-stationary, high-dimensional, and subject to noise [22]. In this study, key frequency-domain features were extracted from alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz) bands using the Discrete Wavelet Transform (DWT), a widely used method for time-frequency signal decomposition (Figure 2). DWT enables multi-resolution analysis by separating signals into approximation (low-frequency) and detail (high-frequency) components, capturing both transient and periodic patterns across scales. The EEG signal was decomposed into six frequency-based features: low and high alpha, beta, and gamma. These features correspond to different mental states—alpha bands are associated with relaxation and cognitive readiness, beta with alertness and stress, and gamma with higher-level cognition and sensory integration. Additional demographic features, including age and gender, were included to account for individual variability. Following wavelet decomposition, Shannon Entropy was computed for each EEG feature to quantify the signal's unpredictability and complexity, serving as an indicator of cognitive or emotional state fluctuations. The entropy values, combined with frequency band statistics (mean, standard deviation, variance), provided a robust, low-dimensional feature representation suitable for machine learning.

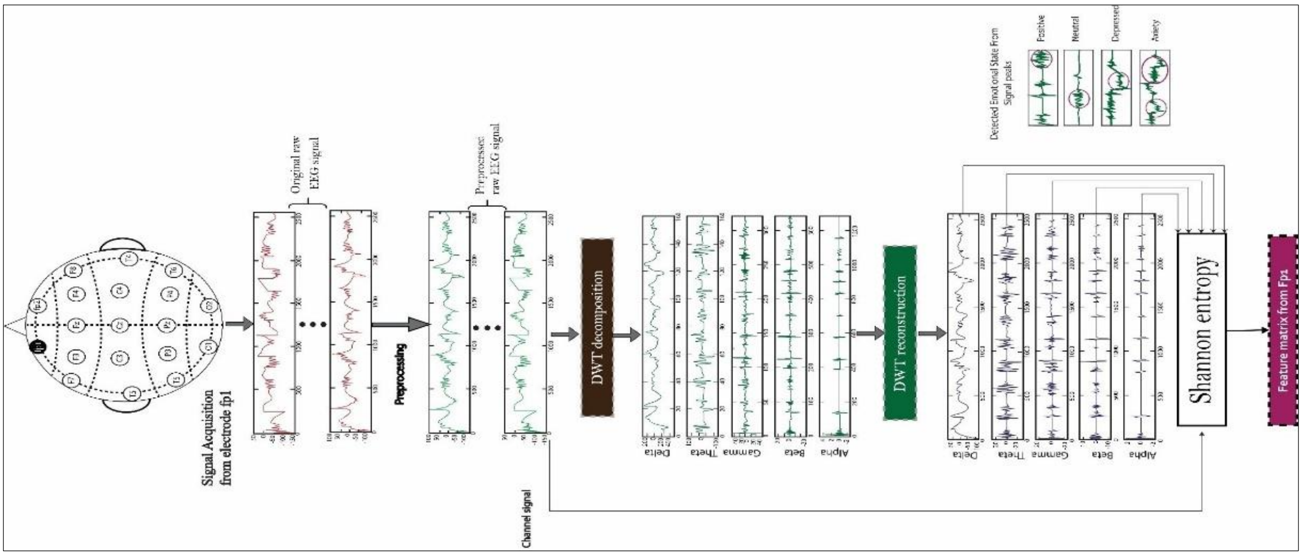

Figure 2 Feature Extraction with DWT (Discrete Wavelet Transform)

3.5. Experimental Models

3.5.1. Baseline Models

To classify EEG-based emotional states, a suite of machine learning models was implemented, each selected for its ability to handle complex, non-linear biomedical data. Hyperparameter tuning was conducted using grid search and 5-fold cross-validation across five dataset variants: the original dataset and those augmented with GAN, SMOTE, ADASYN, and their combination. Support Vector Machine (SVM) with an RBF kernel was employed to handle the non-linear separability of EEG features. The regularization parameter (C = 10) enabled a balance between margin maximization and error minimization, improving class separation in high-dimensional space. A Decision Tree classifier, configured with entropy as the split criterion and a maximum depth of 16, was used for its simplicity and interpretability [32, 33]. Minimum split and leaf sizes were set to 4 to avoid overfitting, ensuring the model remained generalizable. Random Forest, comprising 500 decision trees, leveraged ensemble learning to improve robustness [23]. Bagging and majority voting mechanisms enhanced performance, particularly in the presence of noisy or imbalanced data. The k-Nearest Neighbors (kNN) model used 3 neighbors with Manhattan distance and a ball-tree search algorithm. A distance-weighted voting scheme allowed the model to account for proximity in feature space, making it effective for localized classification. Logistic Regression (LR) served as a baseline due to its interpretability and efficiency. With C = 100 and the SAG solver, LR produced probabilistic outputs and demonstrated competitive performance, particularly on the normalized and entropy-enhanced feature set. Adaptive Boosting (AdaBoost) combined 500 weak learners with a learning rate of 0.1, reweighting misclassified samples iteratively [24], [25]. This ensemble approach improved sensitivity to underrepresented classes and minimized classification bias. Light Gradient Boosting Machine (LGBM), configured with 500 estimators, a learning rate of 1.0, and a maximum depth of 16, utilized histogram-based feature binning and leaf-wise tree growth for efficient and scalable training. Multilayer Perceptron (MLP) was implemented with one hidden layer of 10 neurons and tanh activation [26, 34]. Optimized using the Adam solver with early stopping, MLP effectively captured non-linear dependencies in the EEG data.

3.5.2. One-Dimensional Convolutional Neural Network (NeuroEmotionNet)

To capture both temporal and spectral dynamics of EEG signals, a one-dimensional convolutional neural network (1D CNN) was utilized. Unlike traditional classifiers that rely heavily on handcrafted features, 1D CNNs automatically learn hierarchical feature representations from structured input, making them highly suitable for biomedical signal analysis [27, 35]. The model (Figure 3) was trained with 8-dimensional input vectors per instance, which included frequency band values—low and high alpha, beta, and gamma—along with demographic variables such as age and gender. The architecture consisted of two convolutional layers with 18 and 32 filters, respectively, and utilized kernel sizes of 3 and 5. Each convolutional layer was followed by a ReLU activation function and a max-pooling layer to downsample the feature maps while emphasizing dominant patterns. The 1D convolution operation for an input signal (x) and kernel (w) is defined as Eq. (1), where where K denotes the kernel size. Following convolution, max-pooling reduces the dimensionality while retaining key features such as Eq. 2.

$$y[i] = (x * w)[i] = \sum_{k=0}^{K-1} x[i+k] \cdot w[k] \quad (1)$$

$$y[i] = \max_{0 \le k < p} x\,[i+k] \quad (2)$$

After applying convolution and pooling, the output feature maps were flattened and passed through a fully connected dense layer, culminating in a Softmax output layer for multi-class prediction shown in Eq. 3, where $C = 4$ indicates the four emotional classes. The model was trained using categorical cross-entropy as Eq. 4, where y_i is the ground truth label and $\hat{y}_i$ is the predicted probability.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}, \quad i = 1, \ldots, C \quad (3)$$

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad (4)$$

The 1D CNN is effective for analyzing sequential EEG data because it captures local patterns and temporal dependencies directly. Unlike 2D CNNs, which need data transformation, 1D CNNs work with raw sequences, minimizing computational overhead and complexity. They learn frequency-specific features linked to cognitive states, like increased gamma activity during anxiety or decreased beta power in depression. Its compact design also makes it ideal for real-time emotion monitoring on resource-constrained healthcare devices.

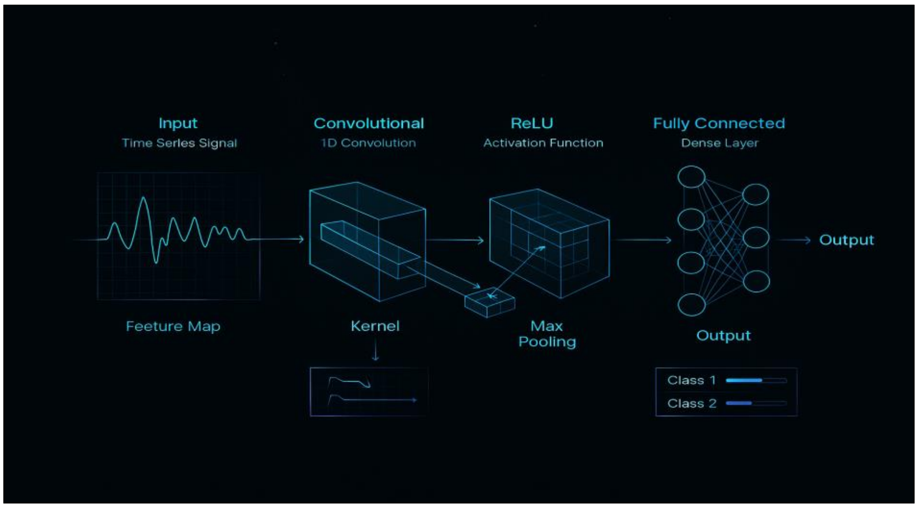

Figure 3 Proposed high-fidelity 1D CNN NeuroEmotionNet architecture

3.6. Evaluation Metrics and Hyper Parameter Settings

The performance of the proposed EEG-based emotion classification models was evaluated using Accuracy, Precision, Recall, F1-Score, Latency, Learning Curves, and Confusion Matrices. These metrics ensured both statistical rigor and interpretability in assessing model behavior across original and augmented datasets. Accuracy quantified overall correctness, while Precision and Recall measured the relevance and completeness of predictions per class. The F1-Score, as their harmonic mean, offered a balanced metric particularly useful for imbalanced classes [20], [21]. All metrics were macro-averaged to treat each emotional state—Positive, Neutral, Anxiety, and Depression—equally. Neural network training employed the Adam optimizer with a learning rate of 0.001 and batch size of 32. A dropout rate of 0.3 was used to prevent overfitting, with training capped at 100 epochs. Early stopping (patience = 5) was applied to halt training when validation performance plateaued. These settings ensured efficient convergence and robust generalization. Hyperparameter tuning for all models was performed via grid search [23], [27], [28]. Parameters such as tree depth and estimators (for Random Forest and Boosting), neighbors (kNN), kernel types (SVM), and hidden layer size or activation functions (MLP) were optimized based on validation accuracy and consistency across datasets [29]. Latency, recorded in milliseconds, reflected inference time and indicated the feasibility of real-time deployment, especially in wearable or embedded EEG systems. Learning curves tracked accuracy and loss across epochs, providing insight into convergence and overfitting. Models exhibiting stable validation trends were considered well-generalized. Confusion matrices offered class-wise analysis, highlighting true positives and misclassification patterns [30], [31]. These helped identify class-specific challenges, such as overlapping between Anxiety and Depression, guiding targeted improvements.

4. Results analysis

4.1. Performance Comparison of Experimental Models

Table 2 offers NeuroEmotionNet and MLP, show superior classification performance, especially with varied and augmented datasets. Traditional models benefit from SMOTE and ADASYN but are generally outperformed by ensembles and deep learning architectures. Combining multiple augmentation techniques enhances model effectiveness and robustness. The 1D CNN outperforms all models, achieving the highest accuracy of 98.41% and an F1-Score of 98.16% on the Combined dataset, indicating strong generalization. The Multi-Layer Perceptron (MLP) also performs well, particularly with ADASYN and the Combined dataset, reaching 97.45% accuracy and a 97.08% F1-Score. These results emphasize the effectiveness of deep learning models with data augmentation. In contrast, simpler models like Logistic Regression and K-Nearest Neighbors (KNN) underperform.

Table 2 Performance of experimental models

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	Original	87.45	86.93	87.1	86.95
	+ GAN	92.63	91.88	92.42	92.14
	+ SMOTE	94.15	93.7	94.01	93.85
	+ ADASYN	93.28	92.45	93.02	92.71
	Combined	94.68	94.12	94.36	94.22
Decision Tree	Original	86.2	85.9	85.76	85.75
	+ GAN	89.31	88.5	89.02	88.65
	+ SMOTE	91.75	91.02	91.44	91.13
	+ ADASYN	90.82	90.2	90.51	90.34
	Combined	92.3	91.68	91.92	91.79
Random Forest	Original	89.52	88.93	89.2	89.01
	+ GAN	93.82	93.1	93.56	93.28
	+ SMOTE	94.91	94.33	94.72	94.49
	+ ADASYN	93.76	93.05	93.48	93.2
	Combined	95.04	94.56	94.83	94.68
kNN	Original	84.75	83.92	84.43	84.02
	+ GAN	88.56	87.93	88.41	88.07
	+ SMOTE	90.38	89.64	90.1	89.82
	+ ADASYN	89.43	88.9	89.2	89
	Combined	91.07	90.34	90.86	90.58
Logistic Regression	Original	82.64	82.12	82.4	82.24
	+ GAN	86.79	86.12	86.4	86.24
	+ SMOTE	89.51	88.93	89.2	89.01
	+ ADASYN	88.37	87.83	88	87.91

	Combined	90.1	89.64	89.92	89.78
AdaBoost	Original	88.45	87.9	88.2	88
	+ GAN	92.32	91.65	92.1	91.84
	+ SMOTE	93.84	93.21	93.6	93.38
	+ ADASYN	92.98	92.31	92.8	92.54
	Combined	94.52	93.92	94.2	94.01
LGBM	Original	89.97	89.2	89.71	89.38
	+ GAN	93.6	92.85	93.42	93.12
	+ SMOTE	95.08	94.52	94.86	94.68
	+ ADASYN	94.2	93.61	93.88	93.74
	Combined	95.65	95.1	95.32	95.18
MLP	Original	91.86	91.4	91.72	91.54
	+ GAN	95.2	94.71	95.08	94.89
	+ SMOTE	96.83	96.4	96.7	96.52
	+ ADASYN	95.97	95.48	95.82	95.65
	Combined	97.45	96.93	97.24	97.08
NeuroEmotionNet	Original	93.1	92.68	92.9	92.78
	+ GAN	96.35	95.94	96.2	96.06
	+ SMOTE	97.92	97.56	97.83	97.69
	+ ADASYN	96.86	96.44	96.72	96.57
	Combined	98.41	98.05	98.28	98.16

Logistic Regression has the lowest F1-Score of 82.24% on the original dataset, and KNN shows variable performance, with a Combined F1-Score of 90.58%. This highlights their limitations in high-dimensional or imbalanced situations. Synthetic data augmentation techniques, especially SMOTE and ADASYN, generally enhance model performance. For example, the F1-Score of the SVM improves from 86.95% to 92.71% with ADASYN. However, GAN-based augmentation is less reliable and sometimes yields poorer results than SMOTE and ADASYN. The Combined dataset approach consistently delivers the best outcomes across models. Ensemble models like Random Forest, AdaBoost, and LightGBM also perform competitively, with AdaBoost achieving a 94.01% F1-Score and LGBM reaching 95.18% on the Combined dataset. These models benefit from data augmentation, showcasing their adaptability.

Table 3 presents the NeuroEmotionNet trained on a richly augmented dataset that achieves state-of-the-art performance in EEG-based emotional state recognition. The findings underscore the effectiveness of hybrid data augmentation in addressing class imbalance and enhancing model generalization, while highlighting the necessity of external validation for practical deployment in clinical or real-time settings. On the original dataset, the model achieved strong baseline results, with F1 scores between 96.4% and 96.7% and MCC values from 95.1% to 95.9%. However, performance for the Anxiety class was lower, indicating its EEG characteristics may overlap with other emotional states. Introducing synthetic data via Generative Adversarial Networks (GANs) consistently improved performance, with F1 scores rising to approximately 97.5–97.8%. This suggests GANs helped increase diversity and allowed better generalization to underrepresent patterns, though improvements for the Anxiety class were minimal. SMOTE and ADASYN further enhanced classification ability by creating balanced class distributions, resulting in increased specificity and recall. PR AUC values reached 98.0% with SMOTE and 98.3% with ADASYN for the Depression class, with MCC values exceeding 97% for most classes. The best results occurred when all three augmentation methods were combined, achieving F1 scores of 98.8% to 99.1% and MCC values up to 98.2%. The Positive and Depression classes achieved specific values of 98.6% and 98.3%, respectively, indicating low false positive rates. This synergy of GAN, SMOTE, and ADASYN improved both the quantity and diversity of training samples. Despite these strong results, caution is needed due to potential overfitting from synthetic sample redundancy or distributional biases. The lack of external validation limits the generalizability of these findings for real-world applications. Future research should include independent testing and explainability techniques to assess whether the model captures physiologically relevant patterns.

Table 3 Classification Report Using NeuroEmotionNet Across All Datasets

Dataset	Class	Accuracy (%)	MCC (%)	PR AUC (%)	F1 Score (%)
Original	Positive	96.5	95.4	96.7	96.6
	Neutral	96.7	95.7	96.8	96.7
	Anxiety	96.3	95.1	96.5	96.4
	Depression	96.8	95.9	96.9	96.5
+ GAN	Positive	97.1	96.5	97.2	97.5
	Neutral	97.5	96.8	97.6	97.8
	Anxiety	97.2	96.3	97.1	97
	Depression	97.3	96.6	97.5	97.3
+ SMOTE	Positive	97.4	96.9	97.7	97.5
	Neutral	97.8	97.2	97.9	97.8
	Anxiety	97.5	96.6	97.4	97.6
	Depression	97.9	97.1	98	97.7
+ ADASYN	Positive	97.5	97	97.8	97.7
	Neutral	97.9	97.3	98.1	97.9
	Anxiety	97.6	96.8	97.5	97.8
	Depression	98.1	97.2	98.3	97.9
Combined	Positive	98.6	97.9	98.8	99.1
	Neutral	98.9	98.2	99.1	99.3
	Anxiety	97.5	97.1	98.4	98.7
	Depression	98.3	97.6	98.9	99.8

4.2. Performance Validation

Figure 4 shows the training and validation loss and accuracy over 50 epochs for a NeuroEmotionNet model across six dataset configurations: Original, GAN-augmented, SMOTE-augmented, ADASYN-augmented, and combined. The results indicate that the model learns effectively, with consistent reductions in loss and improvements in accuracy, suggesting good generalization with minimal overfitting. In the original dataset, loss curves decrease steadily, and training and validation accuracies converge around 90%, indicating some limitations due to the small dataset size and class imbalance. Introducing GAN-generated data accelerates convergence, achieving about 95% accuracy, while keeping training and validation curves aligned, showing GANs enhance learning through realistic variability. SMOTE augmentation improves the learning trajectory further, resulting in loss values that drop quickly and accuracy that exceeds 97%. The validation curve closely follows the training curve, indicating good class balance. ADASYN shows similar trends, but with more fluctuations in validation accuracy, likely due to its adaptive sampling introducing noisy synthetic samples. The most significant performance is with the Combined approach, integrating GAN, SMOTE, and ADASYN. This configuration achieves the lowest loss and highest accuracy across all epochs, with training and validation curves nearly overlapping, resulting in a final validation accuracy of about 99%. This confirms effective learning and strong generalization.

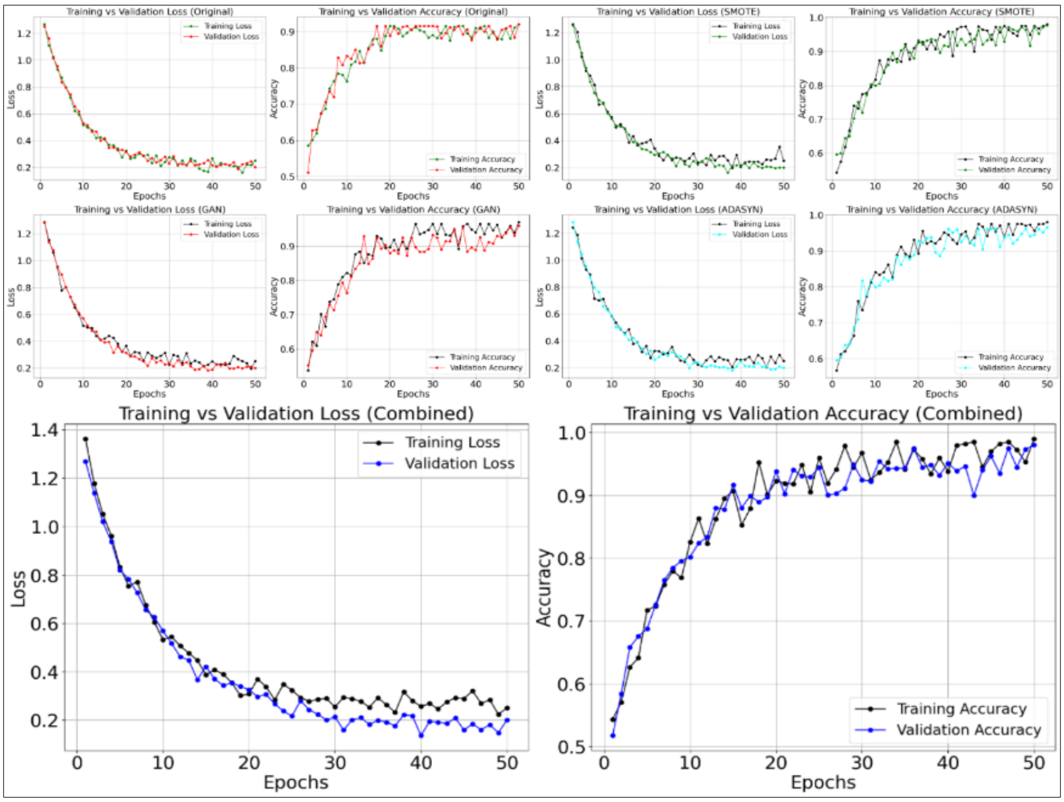

Figure 4 Learning curves of the proposed 1D-CNN model for both datasets

4.3. Web Application

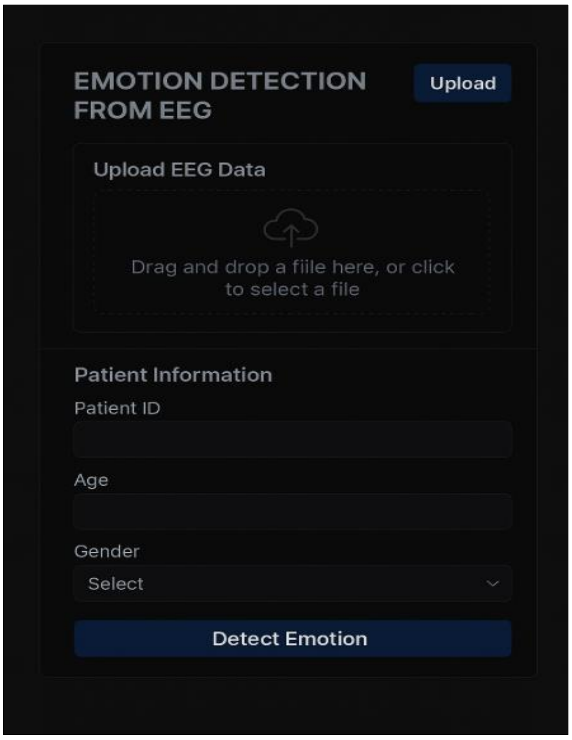

Figure 5 web application demo

The web application titled "Emotion Detection from EEG" exemplifies the practical deployment of the proposed machine learning model (Figure 5). It features a clean, user-friendly interface that enables users to upload EEG data through a drag-and-drop panel, making the system accessible even to non-technical users such as clinicians. This functionality simplifies interaction and supports the model's real-time usability in clinical environments. The interface includes input fields for Patient ID, Age, and Gender, aligning with the demographic features used during training to support personalized predictions. Once the required information is provided, the user can initiate the emotion classification process with a single click via the "Detect Emotion" button, triggering the backend inference pipeline powered by the trained NeuroEmotionNet model. This lightweight, focused design highlights the system's low-latency and high-accuracy capabilities. To further enhance its utility, future improvements may include feedback on prediction confidence, input validation alerts, and the ability to export results. Overall, the application demonstrates the successful translation of the research into a deployable tool for real-time emotion detection in mental healthcare settings.

4.4. State-of-The-Art Comparison

Table 4 provides a clear evaluation of various models used for a classification task, emphasizing both accuracy and real-world applicability. References [8] to [11] utilize traditional machine learning techniques such as RBF-SVM, PCA, DWT, Relief, and ensemble classifiers like RF and KNN. These methods show modest performance, with accuracy scores ranging from 78.96% to 91.3%, reflecting the limitations of handcrafted feature-based approaches. In contrast, references [12] and [13] adopt deep learning-based methods, including a Pyramidal 1D CNN and a VMD-based hybrid model, achieving higher accuracy of 99.1% and 98.7%, respectively. These results illustrate the superior feature extraction capabilities of deep neural networks. However, despite their high performance, none of these previous studies resulted in practical application deployment, as indicated by the "No" in the application column. The proposed model in this study, a NeuroEmotionNet, demonstrates strong and consistent performance with multiple reported results—92.78%, 96.06%, 97.69%, 96.57%, and 98.16%. Although slightly below the peak performance of some previous deep learning models, this method shows robust generalization. More importantly, it stands out as the only model that has been deployed in a real-world application, highlighting its practical relevance and usability. While the table effectively presents comparative accuracy and application status, it would benefit from clearer labeling of the multiple results, consistent formatting of model names, and inclusion of statistical measures like standard deviation. Overall, the proposed model offers a balanced contribution by achieving competitive accuracy and enabling real-world deployment, which distinguishes it from prior works.

Table 4 Performance comparison with previous studies

Reference No.	Proposed Model	Highest Result	App (Yes/No)
[8]	RBF-SVM with PCA on DWT features	91.3%	No
[9]	RF on emotion dimensions	89.96%	No
[10]	DT, SVM, KNN with Relief & PCA	78.96%	No
[11]	PCA + SVM	84.73%	No
[12]	Pyramidal 1D CNN (P-1D-CNN)	99.1%	No
[13]	Kurtosis-based VMD + RF classifier	98.7%	No
Ours	NeuroEmotionNet	92.78, 96.06, 97.69, 96.57, 98.16	Yes

5. Discussion

The EEG-based emotion recognition framework shows excellent performance with classical and deep learning models, particularly the 1D Convolutional Neural Network (NeuroEmotionNet) and Multi-Layer Perceptron (MLP). The NeuroEmotionNet stands out for its high accuracy on the combined augmented dataset, thanks to its ability to learn patterns from EEG signals without manual feature engineering. The MLP also performed well with ADASYN-augmented data, highlighting that simpler models can achieve strong results when fed meaningful features and balanced data. In contrast, traditional classifiers like Logistic Regression and k-Nearest Neighbors (kNN) underperformed on the original dataset, struggling to capture the complex nature of EEG data.

The feature extraction pipeline proved effective in improving model performance. The Discrete Wavelet Transform (DWT) helped break down EEG signals into alpha, beta, and gamma subbands, crucial for distinguishing emotional states. Shannon Entropy added value by measuring signal complexity, often linked to conditions like anxiety and depression. This combination of frequency and complexity features enhanced both classical and deep learning models.

Data augmentation was vital for handling class imbalance and small dataset size. Among the three methods used, SMOTE and ADASYN consistently boosted performance by generating synthetic samples that preserved local data structure and concentrated on underrepresented classes. While GAN-based augmentation showed some benefits, it sometimes lagged behind due to distribution shifts or mode collapse. The best outcomes came from using all three techniques together, demonstrating that hybrid strategies improve the diversity and quality of training data.

A key contribution of this study is the real-time web application for emotion classification using EEG data. Unlike past research limited to algorithmic analysis, this application covers everything from signal acquisition to live prediction. It incorporates demographic info, allowing for personalized modeling, and features an intuitive interface with low-latency predictions, making it ideal for clinical and mental health monitoring.

The proposed method balances performance and deployability. Previous studies achieved higher accuracy but often lacked real-world application or relied on handcrafted features. Our framework not only delivers competitive results but also maintains scalability and interpretability—essential for healthcare integration. Still, there are limitations: reliance on a single institutional dataset affects generalizability, data augmentation may introduce redundancy or overfitting, and distinguishing between closely related emotions like anxiety and depression remains challenging.

Future work will involve validating the system with multi-institutional or cross-subject datasets to improve robustness. Integrating other physiological signals (like heart rate and facial EMG) and contextual data could deepen understanding of emotions. Applying explainable AI (XAI) techniques such as SHAP or Grad-CAM would enhance transparency, aiding clinicians in interpreting model decisions. Additionally, optimizing the application for embedded devices and edge deployment would extend its use in mobile and telemedicine settings.

6. Conclusion

This study introduces a machine learning framework for analyzing EEG signals to improve emotional state detection. It combines frequency-domain decomposition via Discrete Wavelet Transform (DWT), complexity assessment using Shannon Entropy, and demographic information to classify four emotional states: Positive, Neutral, Anxiety, and Depression. The framework utilizes both classical and deep learning models, alongside data augmentation techniques like GAN, SMOTE, and ADASYN, to tackle data scarcity and class imbalance issues. Results show that the 1D Convolutional Neural Network (NeuroEmotionNet) and Multi-Layer Perceptron (MLP) outperform other models, with the NeuroEmotionNet achieving a top F1-Score on the augmented dataset, while demonstrating excellent latency for real-time applications. The augmentation methods significantly enhance classification accuracy, especially for minority classes, proving the effectiveness of synthetic sample generation in biomedical data. A major contribution is the development of a real-time web application for emotion recognition, making the system practical for intelligent mental healthcare. This application provides instant emotion predictions by integrating patient data and EEG signals, marking an advancement over previous offline models. Future research will focus on cross-institutional validation, integrating multimodal data (like physiological and behavioral signals), and incorporating explainable AI techniques for better transparency. This work establishes a foundation for scalable, personalized, and real-time emotion-aware systems to aid early intervention and monitoring in mental healthcare.

Compliance with ethical standards

Disclosure of conflict of interest

There is not conflict of interests.

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