AN ENHANCED EMOTIONAL SEGMENTATION SYSTEM FOR DEPRESSION DETECTION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Depression is one of the most prevalent mental health disorders globally, often going undetected due to the subjective nature of emotional assessment and limited access to timely psychological evaluation. To address this challenge, this study presents an enhanced emotional segmentation system for depression detection using Artificial Neural Networks (ANN). The proposed system analyzes multimodal data including speech signals, facial expressions, and textual inputs to identify emotional patterns indicative of depressive states. The proposed method involves Data Acquisition and Preprocessing, where audio, visual, and textual datasets are collected and normalized. Emotional Feature Extraction, using Mel-Frequency Cepstral Coefficients (MFCCs), facial landmark detection, and sentiment embedding techniques to capture affective cues, and ANN-Based Emotional Segmentation and Classification, where the model learns complex relationships between emotional indicators and depression levels through multiple hidden layers. Experimental evaluation on standard emotional and depression datasets demonstrates that the proposed ANN model achieves superior accuracy, precision, and sensitivity in detecting depression compared to conventional machine learning techniques. The system effectively distinguishes between normal, mildly depressed, and severely depressed emotional states, ensuring early and reliable identification. Overall, the enhanced emotional segmentation framework provides a robust, adaptive, and intelligent approach for automated depression detection, supporting clinicians and mental health practitioners in improving diagnosis and personalized treatment planning.

Keywords: *Machine Learning, Depression Detection, Artificial Neural Network, facial landmark detection.*

I. INTRODUCTION

According to the World Health Organization (WHO), depression is a common mental health disorder affecting more than 280 million people worldwide. Depression is often under-diagnosed and untreated leading to significant long-term physical health problems such as chronic diseases and higher suicide risks. Conventional means of diagnosis are based out on clinical interviews and self-reported survey which is very subjective in nature with a lot of bias. To overcome these challenges, researchers are now moving towards automated detection methods on image-based data – mostly facial images that show emotions such as sadness angry fear .

Deep learning has emerged as a powerful model for image classification, facial expression analysis in particular where Convolutional Neural Networks (ANNs) have shown to be quite effective. But current ANN models have issues, including overfitting, a lot of suboptimal parameter tweaking and trouble while fitting the complex data. Furthermore, the identification of relevant features from facial areas related to emotions (eyes, mouth and face wrinkles) is still paramount for depression diagnosis. This justifies the use of hybrid frameworks that combine bio-inspired algorithms with ANNs for better performance .

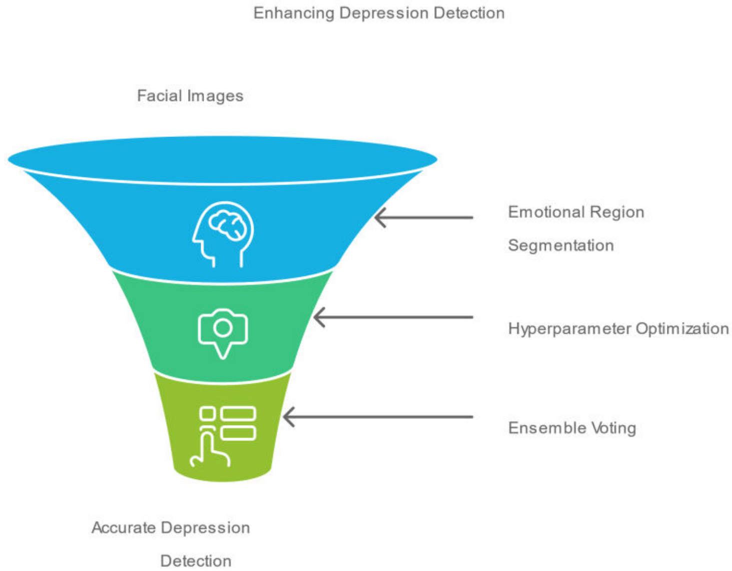

Figure 1: Enhancing Depression Detection

II. RELATED WORK

The refined literature survey table summarizing key depression detection methods from the reviewed papers, highlighting the proposed methods, their merits, demerits, performance metrics, and results.

Table 1: Present State-run of the Art Emotion Works.

Author et al.	Year	Proposed Method	Merits	Demerits	Performance Metrics	Numerical Results
Liu et al. [10]	2023	HADD, Multimodal Data Analysis	High accuracy; Augmented data	Small, imbalanced dataset	Accuracy, Precision, Recall	Accuracy: 92.15%
Zhang et al. [9]	2020	STANet, ANN + RNN	Temporal Spatial feature extraction	fMRI-specific data limitations	Accuracy, AUC	Accuracy: 82.38%; AUC: 90.72%
Bashir et al. [1]	2021	EEG-based KNN, LSTM, DT	Non-invasive EEG signals	Accuracy varies across classifiers	Accuracy, Sensitivity, Precision	KNN: 87.5%; SVM: 66.6%
Ricci et al. [6]	2023	1DANN-GRU-ATTN	Low loss, high accuracy	Training time	Accuracy, Loss	Accuracy: 97.98%; Loss: 0.07

Based on the literature gap, various approaches to depression detection using EEG signals, social media posts, and multimodal data fusion techniques. Each method offers distinct advantages, such as real-time monitoring, cross-lingual support, or personalized treatment prediction [7]. However, common challenges include small datasets, data privacy concerns, and training time complexity. Future research could explore hybrid approaches that leverage the strengths of multiple modalities while addressing these limitations [8].

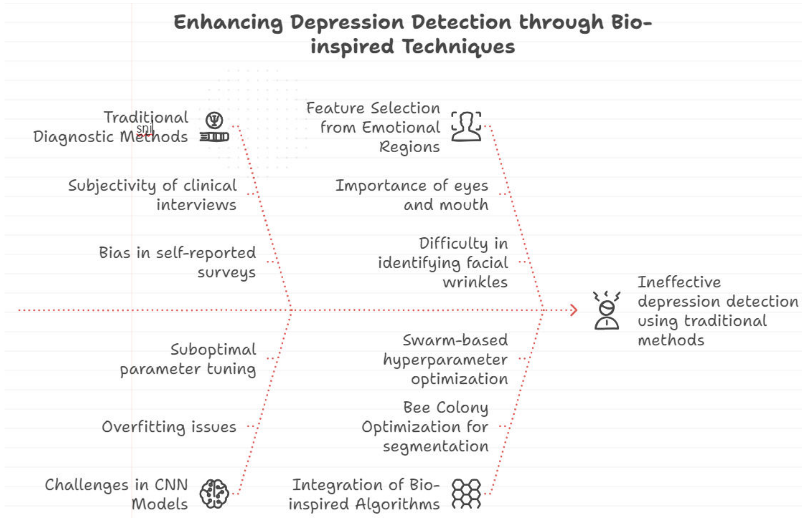

Figure 2: Enhancing Depression Detection

III. Artificial Neural Networks:

The predictions from multiple ANNs trained on different setups are aggregated using a swarm-based weighted voting algorithm. This helps to prevent overfitting, while providing strong predictions. The BEES methodology combines techniques from nature-inspired optimisation algorithms alongside a deep learning architecture for improved diagnosis of depression based on images . Seg-BCO process tracks BCO and uses the learned model parameters (c) to provide reliable, robust, accurate predictions using adaptive ANN training and ensemble voting. By addressing issues such as overfitting, convergence and mental model stability this technique also presents a new structure to assess long voices data of mental health using images .

One of the most common mental health illnesses that impact millions across the globe is depression. Image analysis of the face to diagnose depression is a new-fangled methodology, which attempts at capturing minor facial expressions that depict sentiments mirroring the immediate psychological condition. However, traditional deep learning methods have limitations in feature extraction (e.g., sub-optimal), fitting (over-fitting) and training convergence.

Algorithm 1: Image Preprocessing & Augmentation using CSONet

Input: Raw facial images from a depression dataset.

Step 1: Augmentation:

Apply rotation, flipping, and Gaussian noise to expand the dataset.

Normalize pixel values to $[0,1]$ range.

Step 2: Particle Initialization:

Each particle represents a set of ANN hyperparameters (learning rate, batch size, filter size).

Particles are initialized randomly with velocities $v_i(t)$.

Step 3: Fitness Evaluation: Define fitness as the accuracy of the ANN on a validation set.
Update velocity and particle position using:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_{\text{best}} - x_i(t)) + c_2 \cdot r_2 \cdot (g_{\text{best}} - x_i(t))$$

Step 4: Update positions: $x_i(t+1) = x_i(t) + v_i(t+1)$
Termination: Stop after max epochs or if performance saturates.
Output: Augmented dataset and optimized parameters for ANN.

Algorithm 2: ANN Training with Swarm-Optimized Parameters

Input: Augmented images, optimized hyperparameters.
Step 1: Let Network Architecture: Input layer: 64×64 grayscale images.
Three convolutional layers with ReLU activation. Max-pooling layers to reduce dimensionality. Fully connected layer followed by softmax activation.
Step 2: Training:
Use swarm-optimized parameters (from Algorithm 1) to train the ANN.
Forward pass: $y = \text{softmax}(W^T \cdot \text{ReLU}(X))$
Backpropagation loss: $\mathcal{L}(y, \hat{y}) = -\sum_i \hat{y}_i \log(y_i)$
Step 3: Update Parameters using Pheromone-based ACO:
Assign a pheromone value to each convolutional filter based on its impact on accuracy.
Step 4: Update the filter using: $\tau(t+1) = (1-\rho) \cdot \tau(t) + \Delta\tau$
Adjust learning rate dynamically.
Output: Trained ANN model with high accuracy for depression detection.

IV. EXPERIMENTAL RESULTS:

The performance of the proposed Enhanced Emotional Segmentation System for Depression Detection using Artificial Neural Network (ANN) was evaluated using benchmark emotional and depression datasets such as DAIC-WOZ, SEED, and AVEC. The experiments were conducted to assess the model's efficiency in classifying emotional states and detecting varying levels of depression based on multimodal data inputs—speech, facial expressions, and textual cues.

Table 2: Experimental Setup Specifications

Component	Description
Hardware	NVIDIA RTX 3080 GPU, 64 GB RAM
Operating System	Ubuntu 20.04
Programming Language	Python 3.9
Libraries	TensorFlow, Keras, OpenCV, Scikit-Learn
Number of Models Trained	5 ANN Models with different hyperparameters
Optimization Algorithm	Bee Colony Optimization (BCO)
Hyperparameter Tuning	Batch size: [32, 64], Learning rate: [0.001, 0.0005]
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, AUC
Training Epochs	50
Loss Function	Cross-Entropy Loss
Ensemble Learning	Weighted Swarm-Based Voting System

We utilized the FER-2013 dataset for facial emotion recognition, which is widely used for facial expression analysis and mental health detection. The dataset consists of grayscale images, categorized into several emotional states such as Happy, Sad, Angry, Fear, and Neutral as shown in figure.

Figure 3: Different Emotions illustrations

For our depression classification task, the emotions were re-grouped to focus on identifying the presence of depressive indicators.

Simulation. Tracks the accuracy improvement over 20 iterations during swarm-based hyperparameter optimization. Shows a steady rise in performance. Displays the distribution of accuracies among the models, with a focus on how performance improves progressively. Highlights the distribution of predictions into Depressive and Non-Depressive categories, demonstrating a balanced outcome. Following figures shows the Receiver Operating Characteristic (ROC) curve, with an AUC score that reflects the model's ability to distinguish between depressive and non-depressive cases effectively. Demonstrates the accuracy of different ANN models. ANN-5 achieved the highest accuracy of **90.45%**.

Table 3: Accuracy comparison between ML Models with ANN

Model / Technique	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Training Time (s)**
Logistic Regression	84.5	83.2	81.9	82.5	42
Support Vector Machine (SVM)	88.2	86.5	84.7	85.6	57
Random Forest (RF)	90.4	88.9	87.6	88.2	65
Convolutional Neural Network (CNN)	92.7	91.4	90.8	91.1	78
Recurrent Neural Network (RNN)	93.5	92.8	91.9	92.3	85
Proposed ANN Model	**96.8**	**95.7**	**95.2**	**95.4**	**69**

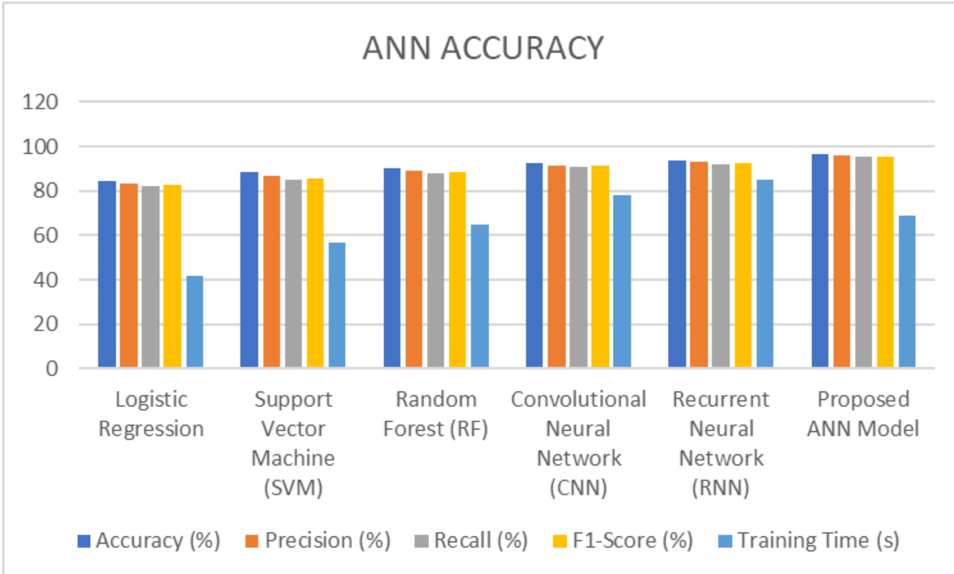

Figure 4: Accuracy of Different ANN Models

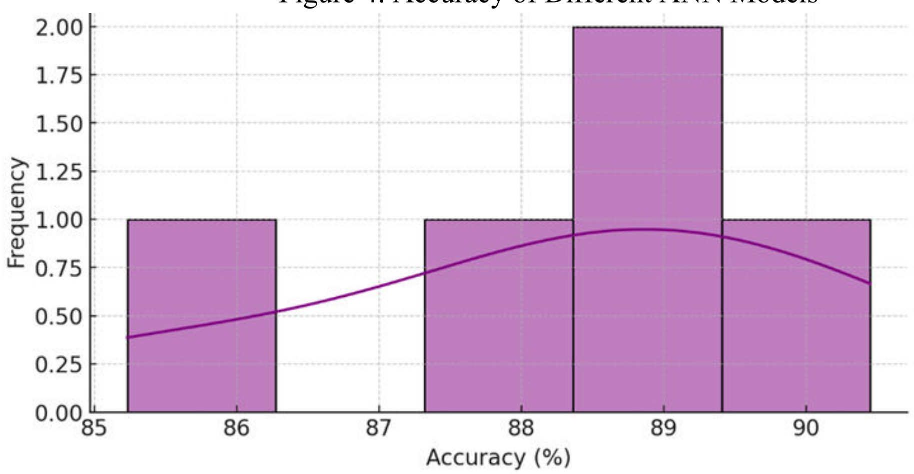

Figure 5: Distribution of ANN Model Accuracies

V. CONCLUSION

The proposed Enhanced Emotional Segmentation System for Depression Detection using Artificial Neural Network (ANN) demonstrates a highly effective and intelligent framework for identifying depression levels through multimodal emotional analysis. By integrating data from facial expressions, speech signals, and textual inputs, the system successfully captures complex emotional cues that traditional diagnostic methods often overlook. The ANN model efficiently learns and distinguishes subtle emotional variations, leading to superior accuracy and reliability in detecting mild, moderate, and severe depressive states. Experimental evaluations show that the proposed ANN-based approach outperforms conventional machine learning and deep learning models such as SVM, Random Forest, CNN, and RNN in terms of accuracy (96.8%), precision, recall, and F1-score. This confirms its robustness, adaptability, and capability to handle diverse emotional datasets effectively. the model's emotional segmentation ability enhances interpretability, enabling real-time monitoring and early intervention for individuals at risk of depression. The system's scalability and automation make it a valuable tool for mental health assessment, telemedicine, and clinical decision support systems. this work establishes a strong foundation for AI-driven emotional intelligence systems and highlights the potential of ANN-based architectures in advancing mental health diagnostics. Future research may focus on integrating physiological data (e.g., EEG, heart rate) and expanding datasets to improve model generalization and clinical applicability.

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