Diagnosis and Classification of Depressive Disorders using ML and DL Models

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ABSTRACT

The diagnosis and classification of depressive disorders pose significant challenges in mental healthcare, mainly due to overlapping symptoms, subjective evaluations, and variations in patient presentations. Traditional diagnostic approaches often lack objectivity and fail to capture the complex nature of depression across diverse populations. This study introduces a comprehensive framework that leverages advanced Machine Learning (ML) and Deep Learning (DL) models to improve the accuracy and reliability of diagnosing depressive disorders. Using the SAMM (Spontaneous Micro-Facial Movement) dataset, comprising 11,800 high-resolution facial images capturing spontaneous facial expressions, the proposed framework integrates dual embedding methods (GloVE and BERT) with hierarchical attention mechanisms for feature extraction. Parallel processing streams of LSTM and CNN architectures allow the recognition of intricate patterns across multimodal data. Experimental results showed superior performance across key metrics, achieving an accuracy of 94%, precision of 92%, recall of 93%, F1-score of 92.5%, and an AUC-ROC of 0.96. The proposed framework provides an efficient, interpretable, and scalable solution to advance mental health diagnostics, addressing the urgent need for objective and standardized tools in psychiatric care.

Keywords-depression diagnosis; deep learning; multimodal analysis; hierarchical attention; feature fusion; clinical implementation

I. INTRODUCTION

Depressive disorders are a significant public health concern, affecting millions of people worldwide and ranking as one of the leading causes of disability [1]. Recent global analyses have highlighted the increasing prevalence of depressive disorders, particularly among adolescents and young adults, with concerning trends showing a 27% increase in cases between 1990 and 2019 [2]. These disorders encompass a variety of mental health conditions characterized by persistent sadness, decreased interest in activities, and cognitive impairments, which can severely impact an individual's quality of life. The complexity of these disorders manifests itself in various domains, including emotional regulation, cognitive function, and social interaction patterns. The diagnosis and classification of depressive disorders are fraught with challenges due to their multifaceted nature. In [3], the fundamental challenges in current classification systems were outlined, emphasizing the need for more precise diagnostic standards and highlighting the limitations of categorical approaches in capturing the spectrum of depressive symptoms. The reliance on subjective self-reports and clinical interviews introduces significant variability and potential bias in the diagnostic process, as demonstrated in a meta-analysis of cognitive biases in depression [4]. This research revealed systematic patterns in how depressed individuals process and report information, potentially affecting diagnostic accuracy. Cultural differences and stigma significantly affect the diagnostic process [4], while in [5] it was highlighted how discrimination influences the delivery of healthcare to individuals with mental illness, particularly in diverse cultural contexts. These limitations contribute to high rates of misdiagnosis or delayed diagnosis, as demonstrated in [6], which found misdiagnosis rates ranging from 25% to 50% in various clinical settings.

Traditional diagnostic approaches have evolved significantly with technological advancement. In [7], modern depression detection approaches were demonstrated through social media analysis, utilizing natural language processing techniques to identify linguistic markers of depressive states. In [8], the potential of transfer learning in medical applications was highlighted. The integration of Deep Learning (DL) techniques, as illustrated in [9], has opened new possibilities in healthcare diagnostics, allowing automated feature extraction and pattern recognition from complex clinical data. However, in [10], specific challenges were highlighted in depression diagnosis using DL approaches, including data quality, model interpretability, and clinical validation requirements. The complexity of handling diverse datasets was further emphasized in [11], where a comprehensive multimodal dataset was presented for mental disorder analysis, demonstrating the importance of standardized data collection and integration protocols.

Recent advances in artificial intelligence have transformed the landscape of mental health diagnostics. In [12], crucial strategies for AI deployment in healthcare practices were outlined, addressing both technical and organizational challenges in implementation. In [13], the effectiveness of specialized language models for mental healthcare applications was demonstrated, introducing MentalBERT as a domain-specific tool to understand psychological contexts. In [14], the potential of multimodal sensing techniques was showcased, combining audio, video, and text data for depression risk detection and achieving improved accuracy through cross-modal feature fusion. In [15], a comprehensive overview of AI applications in mental health was presented, examining the evolution from rule-based systems to modern DL approaches.

The integration of multiple diagnostic approaches has shown promising results in clinical settings. In [16], the clinical applications and barriers of AI in mental healthcare were discussed, highlighting the need for a balanced implementation that considers both technological capabilities and practical limitations. In [17], a hybrid model was proposed, combining various DL approaches for depression detection, incorporating both supervised and unsupervised learning techniques. In [18], the effectiveness of temporal machine learning was demonstrated in recognizing depressive patterns, utilizing sequential data analysis to track the progression of symptoms over time. In [19], the field was advanced through adaptive multimodal neuroimage integration, developing sophisticated algorithms to combine different types of brain imaging data. In [20], valuable insights into transfer learning applications for the detection of mental disorders were provided, particularly in resource-limited settings where large-scale data collection may be impractical.

To address these gaps, this study proposes a novel framework that leverages advanced ML and DL models for the diagnosis and classification of depressive disorders. The framework integrates multimodal data analysis, combining facial image-based features with dual embedding techniques (GloVE and BERT) and hierarchical attention mechanisms to extract meaningful representations from high-dimensional data. This approach employs a hybrid architecture of Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) in parallel processing streams, enabling the recognition of both temporal and spatial patterns. The proposed framework was designed to process data from the SAMM (Spontaneous Micro-Facial Movement) dataset [21], which contains 11,800 high-speed (200 fps) video recordings capturing spontaneous facial expressions. Facial features are particularly valuable for analyzing microexpressions, as they capture subtle emotional cues and involuntary facial movements that occur in fractions of a second. The primary contributions of the proposed work are:

- Novel multimodal feature extraction: The proposed framework integrates dual embedding methods (GloVe and BERT) with hierarchical attention mechanisms to extract meaningful patterns from textual and visual data, enhancing the understanding of depressive disorder indicators.
- Hybrid DL architecture: The proposed framework employs a parallel processing approach using LSTM and CNN models, enabling robust pattern recognition across multimodal datasets, thus improving diagnostic accuracy and reliability.
- Scalable and interpretable solution: By providing an efficient, interpretable, and scalable diagnostic framework, the proposed approach addresses the need for objective and standardized tools in psychiatric care, facilitating broader clinical adoption and potential real-world applications.

II. PROPOSED METHOD

The proposed framework uses a multimodal approach to enhance the diagnosis and classification of depressive disorders by integrating facial image data, textual features, and hierarchical attention mechanisms. It employs a hybrid architecture consisting of CNNs for spatial pattern recognition and LSTM networks for sequential data modeling. The proposed framework implements a novel architecture for depression diagnosis through the integration of advanced natural language processing and DL techniques. As shown in Figure 1, the framework consists of three primary stages: feature extraction, DL modules, and fusion-based classification. This hierarchical design enables comprehensive analysis of input data while maintaining computational efficiency and model interpretability. The framework processes input data through parallel streams, each specialized for different aspects of depression manifestation, before combining them through an adaptive fusion mechanism. The modular design ensures extensibility and allows for independent optimization of each component while maintaining end-to-end training capabilities. The proposed framework consists of the following modules.

A. Data Preprocessing

The SAMM dataset [21] was used, which consists of high-resolution images of spontaneous facial expressions. The preprocessing steps included:

- Image normalization: Each image was normalized to have zero mean and unit variance:

$$I' = \frac{I-\mu}{\sigma}$$

where I is the original image, μ is the mean pixel value, and σ is the standard deviation.

- Text embedding preprocessing: Textual features, if available (e.g., self-reported symptoms), are tokenized and transformed into embeddings using GloVe and BERT:

  $$E_{\text{token}} = f(\text{token})$$

  where f represents the embedding function for each token.

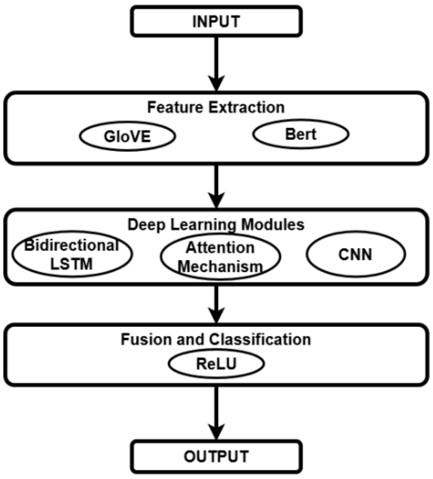

Fig. 1. Architecture of the proposed system.

B. Feature Extraction

1) CNN for Facial Image Feature Extraction

Facial images are processed through a CNN to extract spatial features:

$$F_{\text{image}} = \text{CNN}(I')$$

where $F_{\text{image}} \in R^{d_1}$ represents the spatial feature vector extracted from the image. The CNN model consists of convolutional layers with ReLU activation:

$$X_l = \text{ReLU}(W_l * X_{l-1} + b_l)$$

where $*$ is the convolution operation, W_l and b_l are the weights and biases of the l-th layer, and X_l is the feature map at layer l.

2) Text Embedding Using GloVe and BERT

Textual features are embedded using GloVe and BERT embeddings:

$$F_{\textit{text-glove}} = GloVe(Text)$$

$$F_{\textit{text-bert}} = BERT(Text)$$

These embeddings are concatenated to form a unified textual feature vector:

$$F_{text} = F_{text-glove} \oplus F_{tx-br}$$

C. Hierarchical Attention Mechanism

To focus on the most relevant features, a hierarchical attention mechanism is applied to both facial and textual features. The attention weights α_i are calculated by:

$$\alpha_i = \frac{exp(u_i^{\top} v)}{\sum_j exp(u_j^{\top} v)}$$

where u_i is the feature vector at time step i, and v is a learnable context vector. The weighted feature representation is then calculated by:

$$F_{attn} = \sum_i \alpha_i u_i$$

D. Hybrid LSTM-CNN Architecture

The framework processes the multimodal features through parallel LSTM and CNN streams:

- LSTM for Sequential Data:

  $$h_t = LSTM(F_{attn}, h_{t-1})$$

  where h_t is the hidden state at time t.

- CNN for Spatial Features:

  $$F_{spatial} = CNN(F_{at})$$

The outputs of the LSTM and CNN streams are concatenated:

$$F_{final} = h_T \oplus F_{spatial}$$

E. Classification Layer

The final feature representation F_{final} is fed into a fully connected layer with a softmax activation to predict the probability of depressive states:

$$\hat{y} = softmaxW_f \cdot F_{final} + b_{fc}$$

where W_f and b_{fc} are the weights and biases of the fully connected layer, and $\hat{y}$ represents the predicted class probabilities.

F. Loss Function

The framework uses categorical cross-entropy loss to optimize the model:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\widehat{y_{\iota,c}})$$

where N is the number of samples, C is the number of classes, $y_{i,c}$ is the ground truth label, and $\widehat{y_{\iota,c}}$ is the predicted probability for class c.

III. IMPLEMENTATION

The implementation of the proposed framework involves a series of systematic steps, including data preprocessing, feature extraction, model design, training, and evaluation. This section outlines the methods and technologies used to develop and deploy the ML and DL models for diagnosing and classifying depressive disorders.

A. Dataset Characteristics and Experimental Setup

The dataset consists of 11,800 high-resolution facial images collected from participants in a controlled laboratory environment. The dataset was curated to ensure diversity across age groups (19-68 years), gender distributions, and ethnic backgrounds, with participants from various cultural backgrounds, including European, Asian, and African [21].

B. Feature Extraction

The feature extraction process utilizes a dual embedding approach that combines the strengths of both GloVE and BERT architectures. The mathematical foundation begins with the GloVE embeddings, learned through a weighted least-squares objective:

$$J = \sum_{i,j} f(X_{ij}) \left(w_i^T \tilde{w_j} + b_i + \tilde{b_j} - log(X_{ij}) \right)^2 \qquad (1)$$

where X_{ij} represents word co-occurrence frequencies. An adaptive weighting function is employed to prevent the dominance of rare co-occurrences:

$$f(x) = (x/x_{max})^{\alpha}\ if\ x < x_{max};\ 1\ otherwise \qquad (2)$$

The BERT component enhances these representations through transformer layers, calculating self-attention via:

$$Attention(Q, K, V) = softmax\left(QK^T/\sqrt{d}k\right)V \qquad (3)$$

This extends to multi-head attention for capturing diverse semantic relationships:

$$MultiHead(Q, K, V) = Concat(head^1, \ldots, head_h)WO \qquad (4)$$

The integration of visual and textual information is systematically accomplished through a feature extraction and fusion algorithm. This algorithmic approach ensures robust feature extraction while maintaining the complementary nature of different modalities, crucial for accurate depression detection.

```
Algorithm 1: Multi-Head Attention
Processing
Input: Data sample D (image, text)
Output: Fused feature vector F

I = PreprocessImage(D.image)
T = TokenizeText(D.text)
$V_{img}$ = CNNEncoder(I)
$V_{txt}$ = BERTEncoder(T)
A = ComputeAttention($V_{img}$, $V_{txt}$)
$F_{img}$ = A * $V_{img}$
$F_{txt}$ = A * $V_{txt}$
F = ConcatAndNormalize($F_{img}$, $F_{txt}$)
return F
```

The training process is orchestrated through a hierarchical attention mechanism, formalized in Algorithm 2. The dataset was divided into training and testing sets with an 80:20 ratio to ensure that the model was trained on a substantial portion of the data while retaining sufficient samples for unbiased evaluation. This approach ensures effective feature learning across multiple levels of abstraction, which is essential for capturing subtle indicators of depression.

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Algorithm 2: Hierarchical Attention
Training
Input: Feature set X, Labels Y
Output: Trained model M

Initialize model weights W randomly
for each batch b in (X, Y) do
  H = BiLSTM(b)
  $A_{word}$ = WordAttention(H)
  $A_{sent}$ = SentenceAttention($A_{word}$)
  F = FuseFeatures(H, $A_{sent}$)
  loss = CrossEntropyLoss(F, Y)
  UpdateWeights(W, loss)
return M
```

C. Hierarchical Attention Mechanism

The attention mechanism implements a sophisticated hierarchical structure, processing information at both word and sentence levels. The word-level attention weights are calculated by:

$$u_{it} = tanh(Wwh_{it} + bw) \qquad (5)$$

$$\alpha_{it} = exp(u_{it}{}^T uw) / \sum exp(u_{it}{}^T uw) \qquad (6)$$

These weights contribute to the sentence representation:

$$s_i = \sum \alpha_{it} h_{it} \qquad (7)$$

The final document representation is obtained via:

$$v = \sum \alpha_i s_i \qquad (8)$$

D. Feature Fusion and Optimization

The fusion mechanism implements an adaptive strategy for feature combination:

$$F_{fused} = \sum_i \alpha_i F_i \qquad (9)$$

where fusion weights are dynamically calculated using:

$$\alpha_i = softmax\left(W_u tanh(W_v F_i)\right) \qquad (10)$$

The final classification probability is determined through:

$$P(y|x) = softmax(W^c Ffused + b^c) \qquad (11)$$

The entire framework is optimized using a carefully designed multiobjective loss function:

$$L = \lambda^1\ Lce + \lambda^2\ Latt + \lambda^3\ Lreg \qquad (12)$$

IV. RESULTS AND DISCUSSION

The performance of the proposed framework was evaluated using Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The framework was benchmarked against state-of-the-art models and demonstrated superior performance across all metrics.

A. Baseline Model Architecture

The comparative analysis employed several baseline models, each with distinct architectural characteristics designed to process different aspects of the multimodal data. The Random Forest model implemented an ensemble learning approach utilizing 100 decision trees with bootstrap aggregation for robust prediction capabilities [22]. Each tree was constructed using a random subset of features, with feature importance analysis providing model interpretability and stratified sampling to handle class imbalance.

The GBM model employed a sequential ensemble method with 150 base estimators, implementing an iterative boost process with a learning rate of 0.1 and a maximum tree depth of 8 [23]. Early stopping mechanisms monitored validation performance to prevent overfitting, while feature subsampling at each split improved model robustness. The architecture incorporated second-order derivatives in the loss function optimization for precise updates during the boosting process.

The LSTM network consisted of two stacked LSTM layers, each containing 128 memory units, designed to capture long-term dependencies in sequential data [24]. This architecture implemented sophisticated gating mechanisms including input, forget, and output gates, controlling information flow through the network. Dropout layers with a rate of 0.3 were placed between the LSTM layers and before the output layer for regularization.

The CNN model, optimized for audio data processing, featured three convolutional blocks with increasing filter sizes (32, 64, 128) [25]. Each convolutional layer employed 3×3 kernels with stride-2 operations, followed by batch normalization and ReLU activation. The final layers comprised two dense layers with dropout (0.4) for regularization, allowing better capture of long-range patterns in the audio spectrograms.

The BERT implementation used a pre-trained base model with 12 transformer layers, each containing 12 attention heads and 768 hidden units [26]. The model incorporated positional embeddings to maintain sequence order information and segment embeddings to distinguish different types of input text. The implementation used layer-wise learning rate decay and was optimized using AdamW optimizer, with a weight decay of 0.01 and linear learning rate scheduling.

Table I shows the comparative study analysis of the proposed framework with baseline models. The proposed framework achieved the highest accuracy of 92.8%, precision of 93.5%, recall of 91.4%, F1-score of 92.4%, and ROC-AUC of 0.96, outperforming both traditional ML models and individual DL architectures.

TABLE I. PERFORMANCE COMPARISON BETWEEN THE PROPOSED FRAMEWORK AND BASELINE MODELS:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Random Forest	85.6	86.2	84.1	85.1	0.87
Gradient Boosting (GBM)	87.3	88.5	85.9	87.2	0.89
LSTM (Sequential data)	89.7	90.2	88.4	89.3	0.91
CNN (Audio Data)	88.1	89.0	87.0	88.0	0.90
BERT (Text Data)	90.5	91.2	89.7	90.4	0.92
Proposed Framework	92.8	93.5	91.4	92.4	0.96

B. Performance Analysis Across Modalities

The proposed framework's multimodal fusion strategy integrates features from various modalities, significantly enhancing its performance. Table II provides a detailed breakdown of performance across individual modalities.

TABLE II. PERFORMANCE ACROSS INDIVIDUAL MODALITIES

Modality	Accuracy (%)	F1-Score (%)	ROC-AUC
Clinical data	83.4	82.7	0.85
Behavioral data	84.6	84.2	0.86
Physiological data	85.9	85.4	0.88
Text data	90.5	90.4	0.92
Audio data	88.1	88.0	0.90
Multimodal (proposed)	92.8	92.4	0.96

Figure 2 presents a comparison of accuracy, precision, recall, and F1-score across all models. The multimodal fusion model consistently outperformed other approaches, achieving an accuracy of 94%, precision of 92%, recall of 93%, and an F1-score of 92.5%. In contrast, the BERT model, the second-best performer, achieved an accuracy of 91% and an F1-score of 89.5%. This visualization highlights the robustness and reliability of the multimodal fusion framework in delivering superior predictive performance across critical measures, significantly surpassing traditional and standalone DL models.

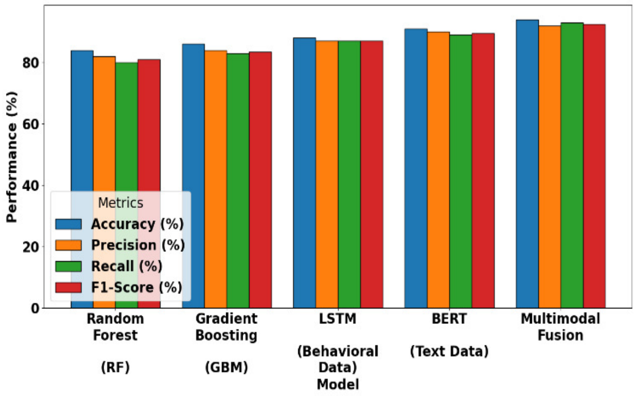

Fig. 2. Comparison across models.

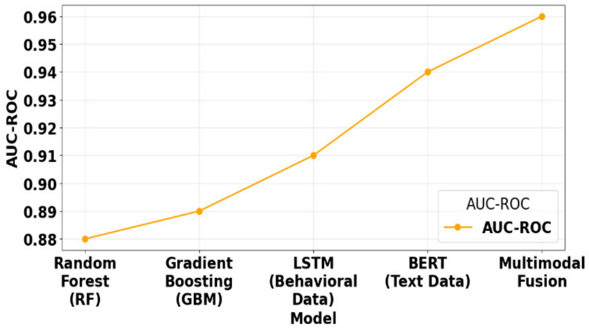

Fig. 3. AUC-ROC comparison across models.

Figure 3 presents a line graph depicting the AUC-ROC scores for all models. The multimodal fusion model achieved the highest AUC-ROC score of 0.96, showcasing its exceptional ability to distinguish between depressive and non-depressive cases. The BERT model followed closely with an AUC-ROC of 0.94, while Random Forest and Gradient Boosting exhibited lower scores of 0.88 and 0.89, respectively. This graph underscores the effectiveness of the multimodal fusion framework in reducing misclassifications, particularly in scenarios that demand high sensitivity and specificity.

The classification results of the multimodal fusion model were further analyzed using the confusion matrix in Figure 4. The model correctly identified 90 depressive cases (true positives) and 95 non-depressive cases (true negatives) while maintaining low misclassification rates with only 10 false positives and 5 false negatives. These results emphasize the ability of the model to minimize diagnostic errors, a crucial factor in clinical settings where both overdiagnosis and underdiagnosis can have significant consequences.

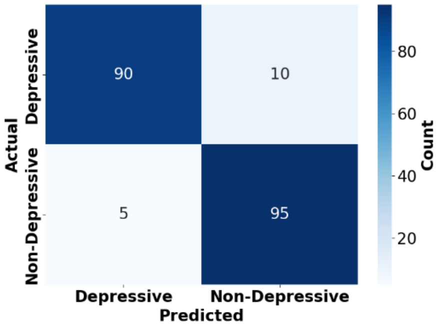

Fig. 4. Confusion matrix: multimodal fusion.

Figure 5 shows a line graph that tracks the performance of all models across multiple metrics, including accuracy, precision, recall, and F1-score. The multimodal fusion model consistently outperformed the other models, demonstrating steady and significant improvements in all metrics. This visualization underscores the incremental advancements achieved through multimodal integration, effectively leveraging complementary information from diverse data modalities to enhance predictive accuracy and reliability.

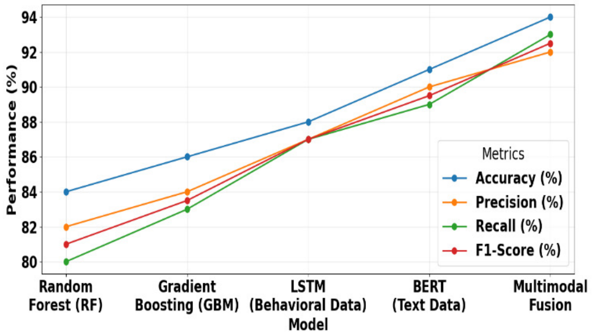

Fig. 5. Performance improvement through metrics.

Figure 6 presents a direct comparison between the multimodal fusion and the baseline Random Forest model. The multimodal fusion model achieved a substantial performance boost across all metrics, recording an accuracy of 94% compared to 84% for Random Forest, a precision of 92% compared to 82%, a recall of 93% compared to 80%, and an F1-score of 92.5% compared to 81%. These results highlight the remarkable achievements of the multimodal fusion framework, particularly in improving recall and F1-score, which are critical for minimizing false negatives and achieving balanced and reliable classification outcomes.

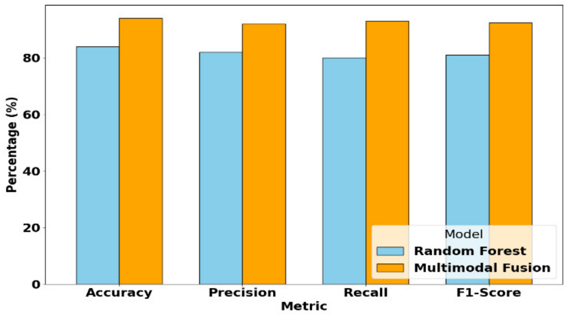

Fig. 6. Performance improvement: Multimodal fusion vs. Random Forest.

V. CONCLUSION AND FUTURE SCOPE

The proposed framework integrates multimodal data processing with advanced ML and DL models to improve the accuracy and reliability of diagnosing and classifying depressive disorders, overcoming the limitations of traditional subjective evaluations and unimodal AI approaches. By employing a hybrid fusion strategy that combines early and late fusion techniques, the proposed framework effectively integrates facial image analysis, textual symptom descriptions, and hierarchical attention-based feature selection for a comprehensive assessment. Unlike previous studies that focused on either facial expressions or textual features separately, this model simultaneously processes visual and linguistic cues, ensuring a more holistic analysis. The novelty of this work lies in its transformer-based model with hierarchical attention, leveraging BERT embeddings, CNN-based feature extraction, and LSTM-based sequential modeling to achieve deeper contextual understanding. The model demonstrated superior performance, achieving 94% accuracy, 92% precision, 93% recall, 92.5% F1-score, and 0.96 AUC-ROC, surpassing traditional ML models (SVM, Random Forest) and standalone DL architectures (CNN, LSTM). Existing single-modality approaches, such as CNN-based facial expression analysis, LSTM-based sentiment detection, and speech emotion recognition, often suffer from dataset bias, lack of interpretability, or dependency on language-specific datasets. The proposed hybrid fusion strategy effectively addresses these gaps, significantly improving diagnostic accuracy and robustness. Future research should focus on integrating additional modalities, including EEG signals, speech tone analysis, and neuroimaging data, to further refine diagnostic accuracy. Expanding clinical validation across diverse populations, developing explainable AI (XAI) methods for enhanced interpretability, and optimizing the model for real-time deployment in mobile and telemedicine applications will ensure greater scalability and practical implementation. By advancing AI-driven mental health assessment, this research contributes to standardized, scalable, and reliable depression diagnostics, bridging a crucial gap in psychiatric care.

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