Volume: 13 Issue: VI Month of publication: June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72715

AI-Based Framework for Early Detection of Depression Using Multimodal Data

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Abstract: Effective intervention and the avoidance of long-term psychological and emotional repercussions depend on early recognition of depression. However, because its early symptoms are subtle, complex, and vary from person to person, they are frequently disregarded [1]. Timely diagnosis is made more difficult by the fact that many persons in the early stages of depression may not seek care or may find it difficult to express their feelings [2]. This study presents a novel artificial intelligence (AI) framework for analysing multimodal data, including text, voice tone, and facial expressions, in order to identify early indicators of depression. The proposed system integrates cutting-edge deep learning modals: BERT is used for understanding contextual linguistic cues [3], CNNs extract significant emotional indicators from facial features [4], and RNNs capture the temporal dynamics and tone shifts in speech [5].

These modalities are fused through a structured data integration strategy, enabling the system to interpret emotional patterns more holistically and accurately. When tested using benchmark datasets like DAIC-WOZ [6], the system shows excellent accuracy and dependability in real-time, non-intrusive identification of depressed signs. Deeper emotional analysis is made possible by the integration of language, auditory, and visual information, which also increases the model's generalizability and robustness across a range of topics [7]. With its scalable, easily available, and objective tools that enhance conventional approaches, this work demonstrates the expanding potential of AI in mental health care [8]. This paradigm facilitates prompt diagnosis and creates opportunities for tailored intervention methods by providing professionals with early, data-driven insights. In the end, it brings us one step closer to a time when technology can help to improve mental health and lessen the prevalence of untreated depression worldwide.

Keywords: Depression Detection, Multimodal Data, Artificial Intelligence, Deep learning, BERT, CNN, RNN, Emotion Recognition, Mental health Technology, DAIC- WOZ

I. INTRODUCTION

Over 264 million people worldwide suffer from depression, a major cause of disability that impairs their mental and physical health as well as their general quality of life [9]. Conventional diagnostic methods, which mostly depend on clinical interviews and self-reported questionnaires, frequently have delayed detection, subjectivity, and practitioner variability [10]. Over time, these restrictions may make it more difficult for people to get timely interventions, which would exacerbate their symptoms. Given how quickly technology is developing, incorporating artificial intelligence (AI) into healthcare offers a revolutionary chance to alter early diagnosis techniques [11].

More objective and proactive methods of identifying mental health illness have been made possible by the growing availability of multimodal data sources, which include text, audio, and visual streams [12]. Powerful models that can integrate and synthesize data from these diverse modalities have emerged as a result of recent developments in deep learning. For instance, teacher-student frameworks using multi-head attention mechanisms have achieved significant accuracy in classifying depressive states by successfully fusing textual and auditory features [13], while architectures such as the Multimodal Object-Oriented Graph Attention Modal (MOGAM) have shown strong performance in analysing social media content for signs of depression [14]. Building on these promising advances, this study suggests a thorough AI-Based framework intended to identify early indicators of depression by integrating multimodal data, which include textual content, vocal traits, and facial expressions. The system makes use of pre-trained modals like Recurrent Neural Network (RNNs) to examine the temporal dynamics of speech [15], Convolutional Neural Network (CNNs) to extract significant visual cues from face expressions [16], and BERT to capture deep contextual language nuances [17]. The algorithm is thus able to identify subtle and complicated emotional patterns that could otherwise go unnoticed by fusing these modality-specific properties using advanced data integration techniques [18]. The suggested paradigm seeks to provide physicians with objective, real-time insights.

II. LITERATURE REWIEW

A. Traditional Approaches for Depression Detection

Depression detection has traditionally relied on clinical interviews, self-reported questionnaires, and structured diagnostic tools like the PHQ-9 and HAM-D scales [19]. While these methods are widely used in clinical settings, they are often subjective, time-consuming, and dependent on patient honesty and clinical expertise [20]. Furthermore, the stigma surrounding mental health frequently leads to underreporting of symptoms, highlighting the need for objective, scalable diagnostic solutions [21].

B. Emergence of AI in Mental Health Diagnostics

Recent advances in artificial intelligence (AI) and machine learning (ML) have paved the way for automated depression detection systems. Early AI-based approaches focused primarily on unimodal data such as text inputs from social media posts or clinical notes [22]. Natural Language Processing (NLP) techniques, especially sentiment analysis and topic modeling, were applied to extract depressive indicators from text [23]. However, these methods struggled with context ambiguity and lacked robustness across diverse user populations [24].

C. Multimodal Data for Enhanced Detection

Recognizing the limitations of unimodal systems, researchers shifted towards multimodal data integration, combining text, audio, and visual cues to achieve richer, more accurate detection. Studies like those using the DAIC-WOZ dataset demonstrated that combining linguistic patterns, speech prosody (pitch, tone, pauses), and facial expressions significantly enhances predictive performance [25]. Audio features, such as Mel-Frequency Cepstral Coefficients (MFCCs), capture paralinguistic cues [26], while facial Action Units (AUs) derived from video data offer insights into emotional states [27]. Recent frameworks utilize feature fusion strategies — early fusion (combining raw features) and late fusion (combining decisions from modality-specific models) [28]. Attention-based fusion techniques have also been introduced to dynamically weigh the importance of each modality depending on context [29].

D. Deep Learning Models in Multimodal Depression Detection

Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), have significantly improved the ability to model complex, nonlinear patterns in depression-related data [30]. CNNs are effective for extracting spatial features from visual data, while LSTMs are ideal for capturing temporal patterns in sequential data like audio recordings [31]. Moreover, the introduction of transformer-based models (e.g., Multimodal Transformer Networks) has enabled the parallel processing of multiple modalities with attention mechanisms that enhance cross-modal understanding [32]. These models are capable of learning intricate relationships between textual sentiment, vocal tone, and facial expression changes, leading to more reliable predictions [33].

E. Challenges in Current Systems

Despite advancements, several challenges remain.

Firstly, most multimodal depression detection models are trained on limited-size datasets like DAIC-WOZ or AVEC, which may not generalize well to broader, real-world populations [34]. Secondly, modality imbalance — where one modality dominates the model's predictions — can reduce overall system robustness [35]. Privacy concerns around the use of personal audio-visual data present additional barriers to clinical application [36]. Furthermore, most current models are black-box systems, offering limited interpretability to clinicians, thus reducing trust and practical usability [37].

F. Ethical and Explainable AI (XAI) in Mental Health

Ethical considerations have become increasingly important. Researchers are now focusing on explainable AI approaches, aiming to make model predictions transparent and understandable for clinical decision-making [38]. Techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are being incorporated into newer systems to address concerns about bias, fairness, and accountability [39]. Privacy-preserving techniques such as federated learning have also been proposed to train models on decentralized data, protecting sensitive patient information while improving model performance [40].

1) Gap Analysis

Although multimodal frameworks have significantly improved depression detection, critical limitations persist. Current models often suffer from overfitting due to small datasets, insufficient cross-modal interaction modeling, and lack of generalization to culturally and linguistically diverse populations. Moreover, few models balance technical accuracy with explainability and ethical design, both of which are crucial for real-world clinical adoption.

2) Summary of Literature Review

The literature indicates a clear shift from unimodal to multimodal approaches in depression detection, with deep learning architectures enhancing the extraction and integration of multimodal features. However, challenges related to dataset limitations, ethical considerations, and model interpretability remain open research areas. Addressing these gaps, this research proposes a robust, ethically-aware, and explainable multimodal AI framework that aims to improve early depression detection and bridge the gap between technological development and clinical usability.

III. METHODOLOGY

A. Overview of the Proposed Framework

The proposed methodology introduces a multimodal AI-based system designed to detect early signs of depression using a combination of textual, audio, and visual data [41]. This integrated approach leverages the unique strengths of each modality to improve diagnostic accuracy and robustness [42]. The framework is constructed to follow a modular pipeline, including data acquisition, preprocessing, feature extraction, modality-specific analysis, multimodal fusion, classification, and explainable prediction [43]. The system aims to overcome the limitations of single-modality models by capturing a broader spectrum of behavioral cues — such as linguistic tone, vocal irregularities, and micro expressions — which have been consistently associated with depressive symptoms in various psychological studies [44]. A visual representation of the proposed architecture is illustrated in the flowchart (see Figure 1), highlighting the parallel processing units for each modality and their subsequent integration for final classification.

B. Data Sources and Acquisition

The proposed framework utilizes benchmark datasets such as DAIC-WOZ and AVEC, which contain real-life interviews annotated for depressive symptoms [45]. These datasets include video recordings, audio tracks, and transcribed text — making them ideal for training and evaluating a multimodal system [46]. To ensure reproducibility and privacy compliance, only de-identified, publicly available datasets were used. Each data sample comprises time-synchronized audio-visual recordings and corresponding speech transcripts [47].

C. Preprocessing Pipeline

Preprocessing is crucial for reducing noise and standardizing input across modalities:

Textual Data: Tokenization, stop-word removal, lemmatization, and sentiment tagging are performed using advanced NLP libraries [48]. Emphasis is placed on extracting context-rich depressive indicators such as use of first-person pronouns, negative adjectives, and cognitive distortions [49].

Audio Data: Audio files are normalized and segmented. Features like MFCCs (Mel Frequency Cepstral Coefficients), pitch variation, jitter, and spectral flux are extracted, which have shown relevance to vocal biomarkers of depression [50].

Visual Data: Video streams are sampled frame-wise, and facial landmarks are extracted using pre-trained deep learning models such as Open Face [51]. Important facial Action Units (e.g., brow furrow, eye closure, lip press) are mapped to identify affective states [52].

D. Feature Extraction and Representation

Each modality passes through a feature extractor designed to capture deep, abstract representations:

Text: Sentences are embedded using transformer-based models like BERT, which captures contextual emotional weight more effectively than traditional word vectors [53].

Audio: Extracted acoustic features are processed through 1D-CNN layers, which learn time-frequency patterns relevant to speech depression markers [54].

Video: CNN-based models are applied on frame sequences to identify micro-expressions and facial affective cues [55].

The extracted features are temporally aligned to ensure synchronization across modalities using timestamps available in the dataset [56].

E. *Multimodal Fusion Strategy*

After modality-specific encoding, a hybrid fusion strategy is applied. This includes both:

Early Fusion, where features are concatenated before classification, and attention-Based Fusion, which dynamically assigns weights to each modality based on contextual importance [57]. This dual-stage fusion enables the model to adapt to cases where certain modalities dominate the depressive cues (e.g., strong visual sadness vs. minimal linguistic indicators) [58].

F. *Classification and Depression Prediction*

The fused representation is passed through a bi-directional LSTM (Bi-LSTM) followed by a fully connected soft max layer to perform binary classification — "Depressed" or "Non-Depressed" [59]. The Bi-LSTM allows the model to capture both past and future dependencies in speech or behavior patterns, which are critical in understanding depressive speech patterns [60]. The classification output is calibrated using threshold tuning and evaluated with cross-validation to ensure generalizability [61].

G. *Explainability and Model Interpretability*

To promote trust and clinical relevance, the model incorporates explainable AI (XAI) mechanisms [62]. Feature importance and decision paths are visualized using SHAP (Shapley Additive Explanations), enabling practitioners to interpret which modalities and features contributed most to each prediction [63]. This interpretability supports the adoption of the system in clinical workflows and ensures ethical transparency, a key requirement in mental health applications [64].

IV. EXPERIMENTAL SETUP

To validate the effectiveness of the proposed AI-based framework for early depression detection using multimodal data, a comprehensive experimental setup was developed. This section outlines the hardware specifications, software tools, dataset characteristics, preprocessing strategies, fusion techniques, and evaluation protocols employed during the research process.

A. *Hardware and Software Configuration*

The experiments were conducted on a high-performance computing environment comprising an Intel Core i7 (11th Gen) CPU, 32 GB RAM, and an NVIDIA RTX 3060 GPU (6 GB VRAM). The system operated on Ubuntu

20.04 LTS. The software environment incorporated Python 3.9, TensorFlow 2.11, Py Torch 1.13, and additional libraries such as scikit-learn, OpenCV, and Librosa. These tools have been widely used in deep learning-based emotion recognition and depression analysis tasks (Tzirakis et al., 2017; Al Hanai et al., 2018).

B. *Datasets Utilized*

Two widely used, benchmark datasets were employed for model training and evaluation:

DAIC-WOZ provides interview data, transcripts, and PHQ-8 scores for depression severity assessment. Its structure enables both unimodal and multimodal analysis in clinical contexts (Gratch et al., 2014). CMU-MOSEI offers a rich repository of annotated audiovisual and textual segments, allowing fine-grained emotion and sentiment analysis across modalities (Zadeh et al., 2018).

C. *Data Preprocessing*

Each modality underwent specialized preprocessing:

Textual Modality: Transcripts were cleaned and tokenized before being passed into the BERT base model to generate contextualized embeddings. BERT's transformer-based architecture is known for its deep language understanding and relevance in psychological language tasks (Devlin et al., 2019).

Audio Modality: Audio clips were normalized and converted into MFCCs and spectral features using Librosa. Such features are commonly adopted in speech-based emotion recognition for depression detection (Al Hanai et al., 2018).

Visual Modality: Facial landmarks, expressions, and action units were extracted using Open Face, an advanced open-source tool that supports real-time facial behavior analysis (Baltrušaitis et al., 2018).

D. *Multimodal Feature Fusion*

After processing, feature vectors were standardized and fused using a hybrid fusion strategy. This approach combined early and intermediate fusion principles, preserving individual modality representations while allowing for cross-modal learning — a method shown to outperform single-stream inputs in related tasks (Tzirakis et al., 2017).

E. Model Training and Baselines

The fused vectors were fed into a 3-layer Multilayer Perceptron (MLP), trained with RELU activation and dropout layers. Alongside, ensemble models such as Random Forest and Gradient Boosting were tested. Traditional classifiers including SVM and Logistic Regression were used for comparative benchmarking. Similar architectures have shown strong performance in multimodal emotion prediction tasks (Zadeh et al., 2018). Cross-validation (5-fold stratified) ensured generalization and robustness of the model.

F. Evaluation Metrics

The framework's performance was measured using:
Accuracy, Precision, Recall, and F1-Score
Confusion Matrix for misclassification analysis
ROC-AUC Curve to evaluate sensitivity-specificity trade-offs
These metrics are standard in health-related machine learning models for class-

V. RESULTS

This section presents a detailed analysis of the experimental outcomes of the proposed AI-based multimodal framework for early depression detection. Multiple machine learning algorithms were evaluated using a fusion of
audio, text, and visual modalities. Results were benchmarked across diverse datasets to ensure robustness and generalizability.

A. Classifier Performance Evaluation

The performance of four widely used classifiers—Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), and Ensemble Learning (EL)—was evaluated based on accuracy, precision, recall, and F1-score. These models were trained on synchronized multimodal features extracted from the DAIC-WOZ, AVEC, and CMU-MOSEI datasets.
Table 1: Classifier Performance Metrics
The ensemble method demonstrated the highest classification performance across all metrics. This aligns with findings in Lee et al. (2021), where ensemble learning significantly improved emotional state prediction due to its capability to reduce variance and generalize better across feature spaces.

B. Dataset-Wise Performance Evaluation

To test the model’s adaptability, it was applied to three major depression-related multimodal datasets. Results showed that larger, more balanced datasets with comprehensive annotations produced superior outcomes.
Table 2: Model Accuracy on Different Datasets
The CMU-MOSEI dataset, offering extensive multimodal annotations, resulted in the highest accuracy, corroborating earlier work by Morales et al. (2021) on large-scale sentiment and emotion corpora.

C. Modality Contribution Analysis

To examine the impact of each individual modality, ablation experiments were conducted. Combinations of text, audio, and visual data were compared to determine their respective and combined influence on classification accuracy.
Table 3: Effect of Modality Fusion
Text data emerged as the most informative single modality, attributed to semantic cues present in depressive speech patterns. However, performance peaked when all three modalities were integrated, supporting the conclusions of Zhang and Xu (2022) regarding the power of multimodal data fusion in emotional analysis.

D. ROC Curve and Confusion Matrix Analysis

A Receiver Operating Characteristic (ROC) curve was generated to evaluate model sensitivity and specificity. The Area Under the Curve (AUC) for the ensemble model was calculated at 0.93, suggesting a strong ability to distinguish between depressed and non-depressed cases.
Figure 1: ROC Curve for Ensemble Learning Classifier
(AUC = 0.93; True Positive Rate vs. False Positive Rate)
The corresponding confusion matrix reveals balanced predictions with a low false positive rate.

Figure 2: Confusion Matrix

These figures validate the model’s precision and recall, consistent with state-of-the-art frameworks in affective computing (Tripathi et al., 2019).

E. Statistical Analysis

Beyond simple classification metrics, additional statistical measures such as Cohen’s Kappa and Matthews Correlation Coefficient (MCC) were computed to evaluate model consistency:

Cohen’s Kappa = 0.78 (substantial agreement) MCC = 0.76 (strong correlation). These scores further emphasize the model's ability to maintain prediction stability across varying user sessions and demographic groups.

F. Summary of Observations

Multimodal Fusion: Integrating all three data types substantially improves prediction accuracy.

Model Robustness: The ensemble model consistently outperformed traditional classifiers.

Dataset Influence: Larger datasets with more detailed annotations produced superior results.

Error Sources: Misclassifications were mostly observed in samples with unclear audio or poor lighting in video, indicating areas for preprocessing improvement.

VI. CONCLUSION

The growing prevalence of depression as a global mental health concern highlights the urgent need for reliable, scalable, and early detection mechanisms. This research has proposed and implemented an advanced AI-based multimodal framework that leverages the integration of audio, visual, and textual data to detect depressive symptoms in individuals at an early stage. The framework utilizes pre-trained models for robust feature extraction and applies ensemble learning techniques to enhance classification performance, achieving notable accuracy and generalization across multiple datasets. Our results demonstrate that multimodal approaches significantly outperform unimodal models, with the ensemble method yielding an accuracy of 89.7% and an AUC of 0.93. Among all tested classifiers, ensemble learning proved most effective due to its ability to combine diverse decision patterns, mitigating the limitations of individual models. Textual features, extracted using language models like BERT, emerged as the most predictive single modality, reflecting the significance of linguistic cues in identifying depressive thought patterns. However, the fusion of text, audio, and visual features provided the most comprehensive insight into users' affective states.

The study further validated the effectiveness of this approach by evaluating performance across standard datasets such as DAIC-WOZ, AVEC, and CMU-MOSEI. This cross-dataset testing confirmed the framework’s generalizability and its potential for real-world applications in clinical, academic, and mobile health environments. In addition to quantitative metrics, the use of tools like ROC curves, confusion matrices, and correlation coefficients provided a holistic view of model reliability. In conclusion, this work offers a significant step toward the development of intelligent, multimodal mental health systems. It emphasizes not only technological innovation but also the ethical importance of timely and non-invasive mental health assessment. With further optimization and integration, such systems could become valuable tools in healthcare, capable of supporting mental wellness initiatives, reducing diagnostic delays, and ultimately improving quality of life for millions at risk of depression.

VII. FUTURE SCOPE

While the current framework demonstrates promising results, there remains substantial room for enhancement and application in broader contexts:

Real-Time Implementation: Future developments should focus on transforming this system into a real-time diagnostic tool for smartphones, chatbots, and telemedicine platforms. This could enable immediate assistance for users in need, especially in remote areas. Explainable AI (XAI): Integrating explainability techniques such as SHAP or LIME can improve transparency and build user trust by providing interpretable decision outputs to clinicians and users.

Cultural and Linguistic Diversity: Expanding the training dataset to include speakers of various languages and from diverse cultural backgrounds will enhance model adaptability and fairness, addressing bias concerns common in AI healthcare tools.

Passive Monitoring Systems: Future research can incorporate wearables and ambient sensors to enable longitudinal tracking of behavior and emotion, offering deeper insights through continuous, non-intrusive monitoring.

Clinical Integration: Collaborating with mental health professionals for validation and user feedback could support the development of clinically certified tools that complement traditional psychological assessments.

Privacy and Ethics: Strengthening data protection protocols and ensuring user consent will be vital in maintaining ethical standards, especially when handling sensitive psychological data. In summary, the proposed framework lays the groundwork for AI-assisted mental health technologies, and with future enhancements, it holds the potential to revolutionize early depression detection across healthcare and societal domains.

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