Multimodal AI For Depression Detection: Integrating Text, Facial Expressions In Social Media Contexts

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***Abstract*—Depression is a globally recognized mental health disorder that affects millions of individuals, often going un-diagnosed due to limitations in traditional screening methods. The growing prevalence of social media platforms has created an alternative space where users express their emotions and thoughts, providing valuable behavioral data for mental health analysis. Most existing AI-based depression detection systems focus on single modalities—primarily text—while overlooking non-verbal cues such as facial expressions that are equally critical in identifying depressive states.**

This paper presents a comprehensive review of recent research in multimodal AI systems that integrate text, image data to improve the accuracy and robustness of depression detection. We explore the use of Large Language Models (LLMs) like BERT and GPT-4 for textual analysis, Convolutional Neural Networks (CNNs) for facial emotion recognitions. A hybrid framework is proposed for fusing these modalities, allowing the system to assess depression risk with high reliability. The review also identifies existing research gaps, such as the need for diverse datasets, real-time implementation challenges, and ethical concerns related to user privacy. Ultimately, this study highlights the significant potential of multimodal AI in supporting early detection and intervention in mental health care, while emphasizing the importance of responsible AI deployment that complements professional psychological assessment.

***Index Terms*—Multimodal AI, Depression Detection, Social Media Analysis, Large Language Models, Facial Emotion Recog- nition, Machine Learning, Mental Health AI, Deep Learning, Explainable AI**

I. Introduction

Depression is a pervasive mental health disorder affecting millions globally, significantly impacting individuals' quality of life, productivity, and social relationships. Early detection and intervention are critical to managing depression effec-tively, yet traditional methods relying on clinical diagnosis often face challenges such as social stigma, lack of accessibil- ity, and subjective bias. In recent years, the rapid proliferation of social media platforms has offered a unique opportunity to understand human behavior, emotions, and mental health at a large scale. Users frequently share their thoughts, feelings, and daily experiences on platforms like Twitter, Facebook, and Instagram, creating rich data sources that can be analyzed to detect signs of psychological distress. The emergence of Artificial Intelligence (AI), particularly machine learning and deep learning techniques, has revolutionized the approach to analyzing complex, unstructured data from social media. Multimodal AI leverages diverse types of data — including text, images and even video — to gain a comprehensive under- standing of users' mental states. By integrating multiple data modalities, multimodal AI systems can capture subtle cues that single-modality models might miss, thereby enhancing the accuracy and robustness of depression detection. This review paper explores the advancements in multimodal AI approaches for detecting depression from social media data. The paper begins by examining the significance of mental health monitoring through non-invasive, automated methods and the potential of social media as a valuable resource for psychological analysis. It then delves into various data modalities used in depression detection, such as textual content analysis, image-based emotion recognition cues from videos notes. Each modality contributes distinct information: textual data can reveal linguistic patterns and sentiment, images can express emotional states through colors and facial expres-sions. Recent studies highlight the effectiveness of combin- ing these modalities using sophisticated machine learning frameworks such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures. These models are designed to process and fuse multimodal features, learning complex patterns indicative of depressive symptoms. Moreover, the review discusses the chal- lenges involved, including data privacy concerns, the ethical implications of monitoring mental health, and the difficulties in obtaining labeled datasets due to the sensitive nature of depression. Additionally, the paper addresses existing gaps in current research, such as the need for standardized datasets, cross- cultural considerations, and the integration of contextual factors like users' demographics and social interactions. The potential for real-time depression detection systems to assist healthcare professionals and provide timely support to at- risk individuals is also emphasized. In summary, this review underscores the transformative potential of multimodal AI in mental health diagnostics by utilizing social media data. It aims to provide a comprehensive overview of the method- ologies, challenges,

and future directions in this emerging interdisciplinary field. As AI technologies continue to advance, their ethical and responsible deployment in mental health mon- itoring holds promise for significantly improving depression detection, intervention, and ultimately, patient outcomes.

II. Related Work

Traditional depression detection research has predominantly relied on text-based AI models. These models use Natural Language Processing (NLP) to analyze linguistic cues in social media posts. For example, depressed individuals are more likely to use negative sentiment words (e.g., ”lonely”, ”hopeless”), personal pronouns (”I”, ”me”, ”myself”), and demonstrate reduced usage of positive emotion words. • Shah et al. (2024) demonstrated that fine-tuned Large Language Models (LLMs) like GPT-3.5 and LLaMA2-7B achieved up to 96• Zhou (2024) applied an NLP-based model on the Weibo dataset, showing promising results in Chinese-language depression detection. • Mayee et al. (2024) used models like RoBERTa and DistilBERT to classify emotional intensity and achieved F1 scores of over 90However, text alone may not always convey a user’s emotional state accurately. Hence, researchers have turned to visual cues, particularly facial expressions, to capture non-verbal indicators of depression. • Jones and Patel (2022) utilized CNN architectures like ResNet and EfficientNet to identify signs such as reduced eye contact, lack of smiling, and neutral facial expressions. Their model reached 85While effective, these models face limitations due to variability in lighting, image quality, and user behavior. This led to the emergence of multimodal systems, which combine text, image inputs for a more complete analysis. •Gupta et al. (2023) proposed a Multimodal BERT model that processed both text and facial expressions, achieving 94•Ghosh Paul (2021) used Type-2 fuzzy logic for analyzing speech emotions, reporting over 97These studies validate that combining modal- ities can outperform single-channel models, but challenges remain in implementation, especially concerning data privacy, bias, and computational complexity.

III. Literature Overview

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have led to the development of various automated systems for detecting depression, particularly through analyzing user-generated content on social media. The literature in this domain can be broadly categorized into three primary streams: text-based models, facial expression analysis, and multimodal systems. Each of these approaches offers unique advantages and faces distinct challenges.

A. Text-Based Approaches

3.1. Text-Based Approaches Text-based models are among the most widely researched methods for depression detection due to the abundance of textual content on social media platforms. These models leverage Natural Language Processing (NLP) techniques to extract psychological indicators from posts, comments, or messages. • Language Features: Studies show that individuals with depression often use more negative affect words (e.g., ”sad”, ”hopeless”), first-person singular pro- nouns (e.g., ”I”, ”me”), and fewer positive words. These lexical features serve as strong indicators of mental health. • Machine Learning Models: Traditional classifiers like Support Vector Machines (SVM) and Na¨ıve Bayes have been used with hand- crafted features. • Transformer-Based Models: More recent studies utilize Large Language Models (LLMs) such as BERT, GPT-4, and RoBERTa, which automatically learn deep contextual representations. For instance, Shah et al. (2024) achieved up to 96• Limitations: Text-only models fail to capture non-verbal expressions and contextual subtleties such as sarcasm, emotion suppression, or tone of voice.

B. Facial Expression Analysis

Facial expression analysis provides important non-verbal cues associated with depression. • CNN Models: Deep learning methods using Convolutional Neural Networks (CNNs) like ResNet, VGG- 16, and EfficientNet have been trained on datasets such as FER-2013 and AffectNet to classify emotions. • Performance: Jones and Patel (2022) achieved 85• Challenges: These models can be affected by environmental factors like lighting, facial obstructions, makeup, and camera quality. Additionally, cross- cultural variations in expression are rarely considered.

C. Multimodal Depression Detection

Multimodal AI systems integrate textual, visual to capture a broader and more accurate representation of an individual’s mental state. • Multimodal BERT: Gupta et al. (2023) devel- oped a model that processes both text and facial image data, achieving 94• Fusion Techniques: o Early Fusion: Combines features from all modalities before classification. o Late Fu- sion: Aggregates predictions from individual modality- specific models. o Hybrid Fusion: Uses attention mechanisms or neural networks to dynamically weigh different inputs. • Advantages: Multimodal models are more robust, less biased, and better suited for real-world applications. • Limitations: These include high computational costs, difficulty in collecting multimodal datasets, synchronization challenges, and privacy concerns.

D. Comparative Summary of Literature

Study Modality Technique Accuracy Limitation Shah et al. (2024) Text LLMs (GPT-3.5, LLaMA2) 96Mayee et al. (2024) Text Emotional intensity via RoBERTa 91Jones Patel (2022)Image CNNs on AffectNet 85Gupta et al. (2023) Text
+ Image Multimodal BERT 94

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The literature strongly supports the potential of multimodal AI systems in enhancing the accuracy and reliability of de- pression detection. While text-only models provide an initial

layer of understanding, they miss non-verbal and contextual in- formation. Facial and speech analyses offer critical emotional insights, and their integration with textual cues leads to better performance. However, challenges such as data privacy, bias, lack of generalization, and high computational requirements still need to be addressed.

IV. Methodology

4. Methodology This section outlines the proposed method- ology for building a multimodal AI system to detect depression from user-generated social media data. The system integrates three major data modalities—text, facial images provide a comprehensive assessment of an individual's mental state. The process includes data collection, feature extraction, model development, and multimodal fusion for final decision-making.

A. Data Collection and Preprocessing

The first step involves gathering multimodal data that repre- sent real-world user behavior on social platforms. Each modal- ity undergoes appropriate preprocessing for noise reduction and format standardization.

1) Text Data: 4.1.1 Text Data • Sources: Social media platforms (Reddit, Twitter, Facebook), mental health forums, chat messages. • Preprocessing: Tokenization, lowercasing, removal of stopwords, lemmatization, and handling of emojis or slang. • Labeling: Posts are labeled as "depressed" or "non- depressed" based on self-reported user data or mental health tags from existing datasets (e.g., CLPsych, eRisk).

2) Image Data: 4.1.2 Image Data • Sources: Selfies, profile pictures, or video frames from user content. • Preprocessing: Face detection, cropping, normalization, and resizing using OpenCV or Dlib libraries. • Data Augmentation: Applied to balance classes and improve model robustness (e.g., rotation, flipping, brightness adjustment).

B. Feature Extraction

4.2. Feature Extraction After preprocessing, features are extracted separately for each modality using state-of-the-art deep learning architectures.

1) Text Feature Extraction: 4.2.1 Text Feature Extraction • Models Used: BERT, RoBERTa, GPT-4 • Features: Contextual word embeddings, sentiment polarity, emotional tone, syntac- tic structure. • Output: Depression probability score based on learned language patterns.

2) Image Feature Extraction: 4.2.2 Image Feature Extrac- tion

• Models Used: CNN-based models such as ResNet-50, VGG-16, EfficientNet. • Features: Facial action units (smile, brow furrow), gaze direction, expression intensity. • Output: Emotional state classification (e.g., sad, neutral, happy) and a depression

likelihood score.

C. Multimodal Fusion and Decision Layer

1) Multimodal Fusion and Decision Layer Once modality- specific features or predictions are obtained, they are integrated to make a unified decision regarding depression risk. *Fusion Strategy:* 4.3.1 Fusion Strategy • Early Fusion: Combines features from all three modalities into a single vec- tor before classification. • Late Fusion: Each model provides a depression score, and results are combined using weighted averaging or ensemble voting. • Hybrid Fusion: Uses attention- based mechanisms or transformer encoders to learn optimal modality weights dynamically.

2) Decision Making: 4.3.2 Decision Making • Classifier: A final dense layer or softmax classifier assigns the input to one of three risk categories: o Low Risk o Moderate Risk o High Risk • Output: A structured risk report that can be used for feedback, alert generation, or passed to human professionals for intervention.

D. System Deployment Possibility

4.3. System Deployment Possibility The proposed model can be integrated into: • Mental Health Chatbots for real-time depression screening. • Telemedicine Platforms to assist clin- icians in remote diagnosis. • Mobile Apps for self- monitoring of mental health by individuals. All modules are designed with privacy-aware processing in mind, where local inference or federated learning can be incorporated to protect user data.be addressed before these systems can be fully adopted in clinical or public health settings. Future research should focus on the development of transparent, fair, and cross- culturally adaptable AI systems that complement—rather than replace— human mental health professionals. In conclusion,

Conclusion

The increasing prevalence of depression, particularly among digitally active populations, calls for innovative, scalable, and accurate diagnostic solutions. Traditional mental health assess- ment methods, while effective, are constrained by subjectivity, time requirements, and limited accessibility. In this context, the integration of Artificial Intelligence with social media data presents a transformative opportunity for early detection and intervention. This paper reviewed recent advancements in depression detection using AI, highlighting the strengths and limitations of text-based, image-based, and speech-based mod- els. While textual analysis through Large Language Models (LLMs) such as BERT and GPT-4 can capture emotional and linguistic cues,

it fails to incorporate non-verbal information crucial for understanding the complete psychological state. Similarly, facial expression and voice analysis using CNNs and acoustic models provide critical affective signals but lack contextual depth. The proposed multimodal AI framework, which fuses text, image, offers a more comprehensive, accurate, and reliable method for depression detection. By leveraging modality-specific features and combining them through intelligent fusion strategies, the system can outperform single- modality models and deliver real-time risk assessments. Such systems hold promise for deployment in mental health chat- bots, mobile diagnostic tools, and remote healthcare services. However, despite these advancements, challenges persist. Ethi- cal concerns around user privacy, cultural and linguistic biases in training datasets, and the explainability of deep learning models must

multimodal AI systems represent a significant step forward in using technology for mental health care. With responsible design and careful deployment, they have the potential to democratize access to early depression detection and support timely, targeted interventions for those in need.

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