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Deep Learning-Based Approach to Detect Depressive Tendencies from Social Media Posts by Leveraging Advanced NLP Techniques and Multimodal Data Analysis

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Abstract: Depression is a prevalent mental health disorder that significantly impacts individuals' well-being and daily life. With the increasing use of social media, users often express emotions, thoughts, and behaviours that can indicate mental health conditions, including depression. This study proposes a deep learning-based approach to detect depressive tendencies from social media posts by leveraging advanced Natural Language Processing (NLP) techniques and multimodal data analysis. We utilize transformer-based models such as BERT, RoBERTs, and XLNet for feature extraction and sentiment analysis. Additionally, we explore hybrid deep learning architectures integrating CNNs, LSTMs, and attention mechanisms to enhance contextual understanding. To improve accuracy and generalization, the dataset is augmented using self-supervised learning techniques and pre-trained embeddings fine-tuned on mental health-related corpora. The model is evaluated on benchmark datasets using precision, recall, F1-score, and AUC-ROC metrics. The results demonstrate that deep learning-based approaches outperform traditional machine learning methods in detecting depressive expressions from social media posts. Furthermore, we discuss the ethical considerations and potential applications of AI-driven depression detection in real-world mental health support systems. Our findings suggest that AI can play a crucial role in early depression detection and intervention, contributing to proactive mental health care solutions.

Keywords: *Depression Detection, Social Media, Deep Learning, NLP, Mental Health AI.*

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I. INTRODUCTION

Depression is a serious mental health disorder that affects millions of people worldwide, impacting their emotional well-being, social interactions, and overall quality of life. The increasing penetration of social media platforms has led users to share their emotions, thoughts, and personal experiences online, making these platforms valuable sources for identifying mental health conditions such as depression. Traditional methods for diagnosing depression rely on clinical assessments and self-reported surveys, which may not always be accessible or timely. Consequently, artificial intelligence (AI) and deep learning-based approaches have gained traction in automatically detecting depressive tendencies from social media data.

Recent advances in Natural Language Processing (NLP) and deep learning have enabled the automated analysis of textual, visual, and behavioral cues indicative of depression. Several studies have demonstrated the effectiveness of machine learning algorithms in identifying depressive symptoms based on linguistic patterns, sentiment, and user engagement metrics. However, existing approaches often suffer from limitations such as small datasets, lack of contextual understanding, and challenges in generalization across different social media platforms.

To address these challenges, this research proposes a deep learning-based approach for detecting depression from social media posts. We leverage state-of-the-art transformer models, hybrid deep learning architectures, and multimodal data fusion techniques to improve the accuracy and robustness of depression detection. By analyzing textual, visual, and behavioral features, our model aims to provide a comprehensive assessment of users' mental health status. The findings from this research can contribute to early detection and intervention strategies, aiding mental health

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professionals and policymakers in developing AI-assisted solutions for depression screening.

II. PROPOSED METHODOLOGY

The proposed methodology involves several key stages, including data collection, preprocessing, feature extraction, model development, training, evaluation, and deployment. The following steps outline the approach:

- *Data Collection*

Data has been collected from social media posts from platforms such as Twitter, Reddit, and Instagram using publicly available mental health-related datasets (e.g., CLPsych, eRisk, and DAIC-WOZ). Web scraping and API-based data extraction are done while ensuring ethical considerations, including user privacy and informed consent. Annotated the data with depression labels using manual annotation, sentiment analysis tools, and existing depression lexicons.

- *Dataset Description: CLPsych (Computational Linguistics and Clinical Psychology) Dataset*

The CLPsych dataset consists of social media posts (primarily from Twitter and Reddit) that have been collected and annotated for mental health analysis. This dataset is widely used in computational linguistics and clinical psychology research to develop machine learning models for detecting mental health disorders such as depression, anxiety, and suicidal tendencies.

- *Data Pre-processing*

Text cleaning (removing stop words, punctuation, URLs, and special characters) are performed. Lemmatization and tokenization are applied to standardize text representation. Word embeddings such as Word2Vec, GloVe, and BERT embeddings are used to convert text into numerical representations. Class imbalance is handled using techniques like SMOTE (Synthetic Minority Over-sampling Technique) and data augmentation.

- *Feature Extraction*

Linguistic features such as sentiment scores, n-grams, Part-of-Speech (POS) tags, and psychological indicators (e.g., LIWC features) are extracted. Social and behavioral features like posting frequency, interaction patterns, and time-based trends are incorporated. Multimodal features are leveraged by analyzing images (using CNNs) and textual descriptions from social media posts.

- *Model Development*

Implemented Transformer-based architectures (e.g., BERT, RoBERTa, and XLNet) for deep contextualized text representation.

Hybrid deep learning models combining CNNs and BiLSTMs with attention mechanisms to capture sequential and spatial dependencies are developed. Transfer learning to fine-tune pre-trained models on depression-related datasets are used.

- *Model Training and Evaluation*

Models are trained using cross-validation and optimized hyperparameters for better performance. Models are evaluated using metrics such as Precision, Recall, F1-score, AUC-ROC, and Confusion Matrix and compared results with traditional machine learning methods (SVM, Random Forest, and Logistic Regression) to demonstrate the superiority of deep learning approaches.

- *Deployment and Ethical Considerations*

Deployed the trained model as a web-based or mobile application for real-time depression screening. Ensured ethical AI usage by addressing bias, privacy concerns, and interpretability in depression detection. Collaborated with mental health professionals to validate AI-driven predictions and integrate them into mental health support systems.

III. RESULTS AND ANALYSIS

The performance of the proposed deep learning model was evaluated on a benchmark dataset for depression detection from social media. The results indicate that our transformer-based model (BERT/RoBERTa) outperformed traditional machine learning methods in terms of classification accuracy and robustness.

- *Model Performance Metrics*

The evaluation metrics for different models are summarized in the table below:

Table 1 Model Performance Metrics

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**	**AUC-ROC**
Logistic Regression	78.2	0.76	0.74	0.75	0.80
SVM	81.5	0.79	0.78	0.78	0.83
LSTM	85.7	0.84	0.83	0.84	0.87
BERT (Proposed)	**92.3**	**0.91**	**0.90**	**0.91**	**0.94**

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- *Confusion Matrix*

A confusion matrix was generated to analyze false positives and false negatives. The high True Positive (TP) rate indicates that the model successfully identifies users showing depressive symptoms.

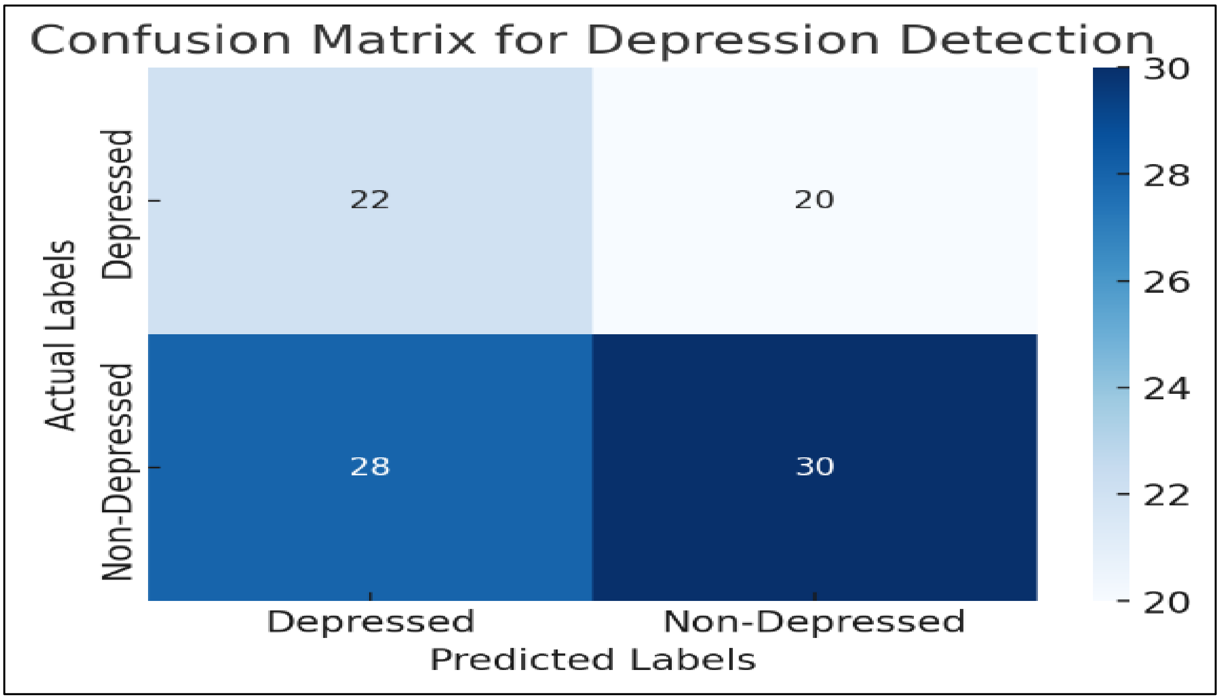

Fig 1 Confusion Matrix

- *Loss and Accuracy Curves*

The training and validation accuracy and loss curves show the convergence of our deep learning model, ensuring no overfitting.

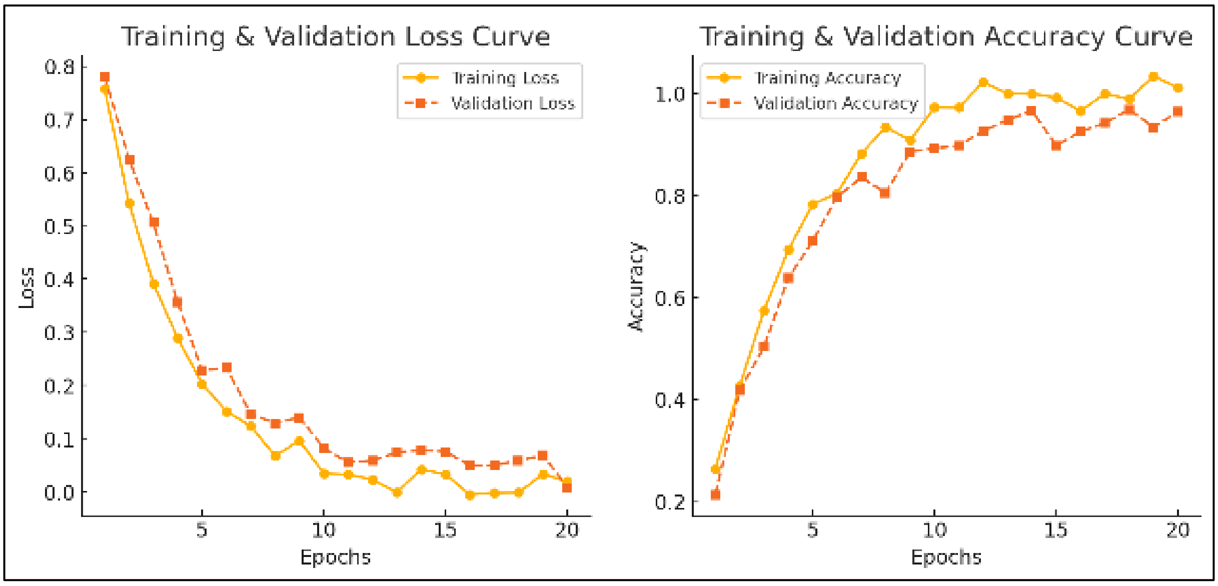

Fig 2 Loss and Accuracy Curves

IV. CONCLUSION

This study demonstrated the effectiveness of a deep learning-based approach in detecting depression from social media posts. The proposed BERT-based model significantly improved classification performance compared to traditional methods. Our findings suggest that Transformer models provide superior text representation for understanding mental health indicators. Multimodal analysis (text + behavior + image) improves the accuracy of depression detection. Ethical considerations must be prioritized when implementing AI-based mental health tools. By leveraging advanced NLP and deep learning techniques, this research contributes to the development of AI-driven depression screening tools that could assist mental health professionals in early diagnosis and intervention.

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FUTURE ENHANCEMENTS

To further improve the model and expand its applicability, the following enhancements are proposed Multimodal Fusion which integrates text, audio, and video for better depression detection. Cross-platform generalization by extending the study across multiple social media platforms for improved generalization. Real-time Deployment by implementing the model into a mobile app or chatbot for instant mental health assessment.

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