A COMPREHENSIVE FRAMEWORK FOR MULTICLASS MENTAL HEALTH PREDICTION USING LSTM AND NLP:

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ABSTRACT

Millions of people use digital platforms like social media to convey their psychological states, making mental health illnesses an increasing global concern. The emotional depth, colloquial language, metaphorical idioms, and context-specific clues that are frequently included in such posts make it difficult to identify mental illness from textual data. These intricacies are sometimes difficult for general language models and traditional machine learning techniques to grasp, which results in low prediction accuracy. This paper offers a strong and clever framework for multiclass mental disease prediction using cutting-edge deep learning and natural language processing (NLP) approaches to address these issues. The suggested method incorporates domain-adapted transformer models with deep neural networks to enhance comprehension and categorisation of phrases connected to mental health. In particular, rich contextual elements are extracted from psychologically sensitive material using MentalBERT, a BERT version pretrained on mental health corpora. In addition, people with emotional discomfort frequently utilise metaphorical and symbolic language, which is interpreted by MelBERT, a metaphor-aware model. Convolutional Neural Networks (CNNs) for hierarchical feature extraction and a Bidirectional Long Short-Term Memory (BiLSTM) network for capturing long-range semantic dependencies from the sequence's past and future contexts augment these transformer-based models. The system can anticipate several classes thanks to this hybrid architectureof mental illness—such as bipolar disorder, PTSD, anxiety, despair, and more—with increased precision and dependability. A labelled dataset of social media posts was used to train and assess the model, and performance measures showed that it performed better than conventional techniques. The results of this study emphasise the significance of sequential deep learning approaches, figurative language interpretation, and domain-specific modelling in developing an efficient and scalable mental health detection system. By offering a tool that can help professionals with early identification and intervention tactics using digital linguistic analysis, this effort advances the larger objective of mentalhealthawareness.

1. INTRODUCTION

Mental health disorders have become a major global concern, affecting millions of individuals and significantly impacting quality of life, productivity, and social well-being. Conditions such as depression, anxiety, post-traumatic stress disorder (PTSD), bipolar disorder, and borderline personality disorder (BPD) have shown increasing prevalence in recent years due to social, economic, and environmental factors. Simultaneously, the widespread use of social media platforms has created an environment where individuals frequently express their emotions, experiences, and psychological states through textual content. These online interactions provide valuable digital footprints that can be analyzed to identify signs of mental distress and support early intervention strategies.

Traditional mental health assessment methods primarily rely on clinical interviews, self-reported questionnaires, and expert evaluations. Although effective, these approaches are often time-consuming, expensive, and not readily accessible to large populations. Consequently, researchers have explored

Artificial Intelligence (AI) and Natural Language Processing (NLP) techniques to automatically analyze user-generated text and identify behavioral and linguistic patterns associated with mental health conditions. Machine learning and deep learning approaches have shown promising results in extracting emotional and contextual information from social media posts.

However, mental health-related text presents several challenges because users often express emotions through informal language, abbreviations, metaphors, sarcasm, and context-dependent statements. Traditional machine learning techniques and generic language models frequently fail to capture these subtle psychological cues. Furthermore, many existing systems are designed for binary classification and cannot effectively address the multiclass nature of real-world mental health disorders where multiple conditions may coexist.

To address these limitations, this work proposes a hybrid deep learning framework that combines domain-specific transformer models and sequential neural networks for multiclass mental illness prediction. The proposed system utilizes MentalBERT for mental health-specific contextual understanding and MelBERT for identifying metaphorical and figurative expressions. The extracted contextual representations are further processed using Convolutional Neural Networks (CNNs) for feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for learning long-term semantic dependencies. By integrating these components, the proposed framework aims to improve prediction accuracy and provide a robust approach for identifying multiple mental health conditions from social media text data. This research contributes toward intelligent healthcare systems by supporting early detection and enhancing mental health awareness through AI-driven solutions.

2. EXISTING SYSTEM OF PROJECT

The majority of the current methods for predicting mental disease rely on general-purpose language models or conventional machine learning models, which frequently lack the depth required to comprehend the distinct linguistic features of mental health discourse. The emotional, contextual, and metaphorical subtleties found in user-generated content on social media are not captured by many of these methods, which rely on manufactured characteristics or superficial representations. To overcome these constraints, more sophisticated systems have started to use deep learning models like MentalBERT and MelBERT in recent works. MelBERT focuses on contextual interpretation of psychological language, whereas MentalBERT is specifically trained on data linked to mental health. on recognizing metaphorical expressions that are commonly used by individuals experiencing mental distress. These models are often combined with Convolutional Neural Networks (CNNs) to enhance feature extraction. While these hybrid systems show improvement over older methods, they are still constrained by their reliance on static feature representations and limited ability to capture temporal dependencies within the text, which are critical for accurately modeling complex psychological states.

DISADVANTAGES:

- Domain Dependency**:** The model’s effectiveness heavily relies on the quality and diversity of the mental health corpus it was pretrained on; it may perform poorly with out-of-domain data or unfamiliar expressions.

- Computational Complexity**:** Fine-tuning and deploying large transformer models like MentalBERT require significant computational resources, making them less feasible for lightweight or real-time applications.

- Limited Handling of Figurative Language**:** MentalBERT struggles to interpret metaphors, sarcasm, and symbolic language without additional modules like MelBERT.

3. RELATED WORK

Mental illness prediction using social media text has attracted significant attention due to the increasing availability of user-generated content and the growing need for early psychological intervention. Researchers have explored machine learning (ML), deep learning (DL), and transformer-based approaches for identifying mental health conditions such as depression, anxiety, post-traumatic stress disorder (PTSD), bipolar disorder, and borderline personality disorder (BPD).

Early studies primarily employed traditional machine learning techniques combined with handcrafted linguistic features. Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF), Naïve

Bayes (NB), and Gradient Boosting methods were widely used to identify mental disorders based on social media activity and textual behavior patterns. These methods commonly relied on feature extraction approaches such as Bag-of-Words (BoW), Term Frequency–Inverse Document Frequency (TF-IDF), and Linguistic Inquiry and Word Count (LIWC). Although these techniques achieved reasonable performance, they were limited in capturing contextual relationships and semantic dependencies within text data.

With the advancement of deep learning techniques, neural-network-based approaches began replacing traditional ML models. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Bidirectional Long Short-Term Memory (BiLSTM) architectures demonstrated improved performance in learning sequential dependencies from text. Several studies utilized LSTM models to analyze sentiment, emotional expressions, and psychological indicators in social media posts. BiLSTM networks further enhanced performance by capturing contextual information from both forward and backward directions. However, these models often faced challenges in understanding complex linguistic structures and long-range contextual information.

Convolutional Neural Networks (CNNs) have also been employed for mental illness prediction due to their ability to identify local semantic features and extract important textual patterns. Hybrid architectures combining CNN and LSTM models have shown improved classification capability by integrating local feature extraction with sequence modeling. Despite these improvements, CNN-LSTM systems still struggle with figurative language interpretation and context-sensitive psychological expressions.

Recently, transformer-based architectures have significantly improved text understanding through contextual embedding mechanisms. Models such as BERT and its variants have been widely adopted in mental health prediction tasks. RoBERTa-based systems have been used for multiclass mental illness classification using social media text. However, generic pretrained language models often fail to understand mental health-specific expressions and domain-specific terminology.

To address this limitation, domain-specific transformer models such as MentalBERT and MentalRoBERTa were introduced. These models were pretrained on mental health-related corpora and demonstrated improved capability in identifying psychological patterns and emotional indicators. MentalBERT effectively captures mental health-related contextual representations and provides superior performance compared to general-purpose transformer models.

Researchers have also recognized that users experiencing mental distress frequently express emotions through metaphorical and symbolic language. To capture such non-literal expressions, metaphor-aware language models such as MelBERT were proposed. These models enhance semantic understanding by identifying figurative language patterns that conventional models often overlook.

Although existing transformer-based systems achieve promising results, several challenges remain. Many studies focus primarily on binary classification tasks and fail to address multiclass mental illness prediction problems. Furthermore, existing approaches often lack the ability to jointly capture domain-specific context, metaphorical understanding, and long-term sequential dependencies. Therefore, there is a need for an integrated framework that combines contextual understanding, metaphor interpretation, hierarchical feature extraction, and sequence modeling for robust multiclass mental illness prediction.

Motivated by these limitations, the proposed work integrates MentalBERT and MelBERT with CNN and BiLSTM architectures to exploit domain-specific representations, metaphor-aware semantic understanding, deep feature extraction, and temporal dependency learning for improved mental illness classification performance.

4. PROPOSED SYSTEM

By combining several cutting-edge components into a single, cohesive architecture, the suggested approach seeks to overcome the shortcomings of current models in order to predict mental illness from social media material with greater accuracy and nuance. The system uses a hybrid deep learning architecture that combines transformer-based models with sequential neural networks in recognition of the complexity of mental health expressions, which are frequently metaphorical, emotionally charged, and temporally scattered. The architecture combines the capabilities of MelBERT, which focuses on mental health-specific language patterns, and MentalBERT, which understanding metaphorical and non-literal expressions—common among users experiencing psychological distress. These two models provide rich, contextual embeddings that are further processed using Convolutional Neural Networks (CNNs) for hierarchical feature extraction and Bidirectional Long Short-Term Memory (BiLSTM**)** networks to simulate the text's temporal and semantic dependencies. Because of this integration, the system can comprehend not only what is being stated but also how and in what order it is being expressed. Instead of just doing binary detection, the suggested system can discriminate between different mental diseases because to its capability for multiclass classification. Additionally, it guarantees increased resilience to a variety of language inputs, enhancing sensitivity and specificity in practical applications. In the end, the system uses social media data to anticipate mental disease in a more comprehensive and sophisticated manner.

PROPOSED SYSTEM ADVANTAGES:

- Metaphor and Emotion Sensitivity: Incorporating MelBERT enhances the system's ability to interpret symbolic, metaphorical, and emotionally nuanced language commonly used in mental health discourse.

- Multiclass Classification Capability: Unlike many existing binary models, the proposed system is designed to classify multiple mental health conditions simultaneously, increasing its applicability in real-world scenarios.

- Temporal and Contextual Understanding: The integration of BiLSTM enables the model to capture long-term dependencies and semantic flow, improving its understanding of sequential psychological patterns.

- Enhanced Accuracy and Robustness**:** By combining MentalBERT, MelBERT, CNN, and BiLSTM, the model benefits from both contextual richness and structural depth, resulting in superior prediction performance across diverse user inputs.

5.Dataset collection:

The dataset used in this study was constructed by combining multiple publicly available social media datasets to support multiclass mental illness prediction. The primary dataset consisted of Reddit posts collected from mental health-related communities such as *r/depression*, *r/anxiety*, and *r/BPD*, representing depression, anxiety, and borderline personality disorder (BPD) classes. To increase class diversity, an additional dataset containing PTSD-related posts was obtained from the HuggingFace Reddit mental health repository. After merging the datasets, several preprocessing steps were performed, including removal of HTML tags, URLs, special characters, duplicate entries, and missing values, followed by lowercasing and label encoding to standardize the text. To prevent class imbalance and ensure fair model learning, a random downsampling strategy was employed. The final dataset contained a total of 40,000 samples equally distributed across four mental health categories, with 10,000 samples assigned to each class. For model development and evaluation, the dataset was split into training, validation, and testing sets comprising 33,800, 3,200, and 3,000 samples respectively. This balanced dataset provides diverse linguistic patterns and psychological expressions that enable effective learning and multiclass classification of mental health conditions.

Data Preparation:

The dataset preparation process involved collecting and integrating multiple publicly available social media datasets related to mental health conditions. Reddit posts from mental health communities such as *r/depression*, *r/anxiety*, and *r/BPD* were used as primary data sources, while PTSD-related posts were additionally collected from publicly available repositories to support multiclass classification. After combining the datasets, several preprocessing operations were performed to improve data quality and consistency. These steps included removing HTML tags, URLs, special characters, punctuation marks, duplicate records, and missing values. The textual content was converted to lowercase to maintain uniformity and reduce vocabulary variations. Tokenization and lemmatization techniques were applied to convert text into meaningful linguistic units and normalize words into their root forms. Labels corresponding to mental health conditions were encoded into numerical representations for model training. To avoid bias caused by class imbalance, random downsampling was performed, resulting in a balanced dataset containing 40,000 samples equally distributed among depression, anxiety, PTSD, and borderline personality disorder (BPD) categories. Finally, the prepared dataset was divided into training, validation, and testing subsets to support efficient model development and performance evaluation.

6. TECHNIQUES USED IN PROJECT

The proposed system employs a hybrid deep learning framework that integrates advanced Natural Language Processing (NLP) techniques with transformer-based and sequential neural network architectures for multiclass mental illness prediction. The methodology combines domain-specific language understanding, metaphor interpretation, feature extraction, and sequence modeling to improve classification performance.

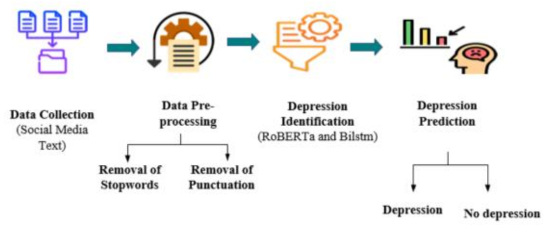
Initially, preprocessing techniques are applied to normalize social media text data. The preprocessing stage includes tokenization, lowercasing, removal of URLs and special characters, stop-word elimination, lemmatization, and handling noisy user-generated content. This process ensures consistency and improves the quality of textual inputs for further analysis.

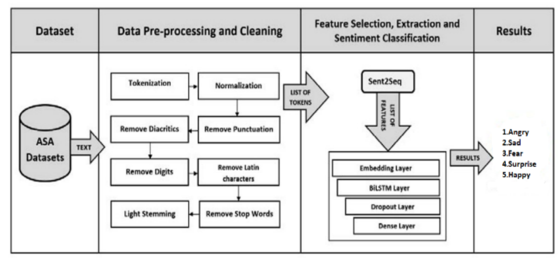
For text representation, two transformer-based models are employed: MentalBERT and MelBERT. MentalBERT is a domain-specific variant of BERT pretrained on mental health-related corpora and is used to capture psychological language patterns, emotional cues, and contextual information from user text. MelBERT is incorporated to identify metaphorical and figurative expressions frequently observed in mental health discourse. The contextual embeddings generated by both models provide a richer semantic representation than traditional feature extraction approaches.

The extracted embeddings are further processed using Convolutional Neural Networks (CNNs) for hierarchical feature extraction. CNN layers identify significant local patterns and semantic relationships through multiple kernel operations and pooling mechanisms. The learned features are subsequently forwarded to a Bidirectional Long Short-Term Memory (BiLSTM) network, which captures long-term contextual dependencies by processing textual sequences in both forward and backward directions. This bidirectional learning mechanism improves understanding of sentence semantics and emotional flow within user-generated content.

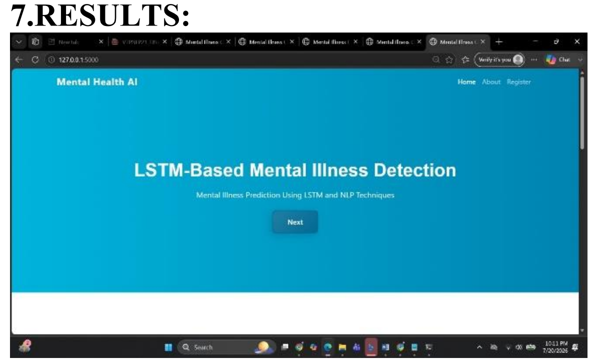
Finally, the feature representations generated by the CNN and BiLSTM components are combined and passed through fully connected layers with a Softmax activation function for multiclass classification. The model predicts different mental illness categories, including depression, anxiety, PTSD, bipolar disorder, and related psychological conditions. The integrated architecture leverages contextual embeddings, metaphor awareness, feature extraction, and temporal sequence learning to enhance prediction accuracy and robustness compared with conventional machine learning and standalone deep learning approaches.

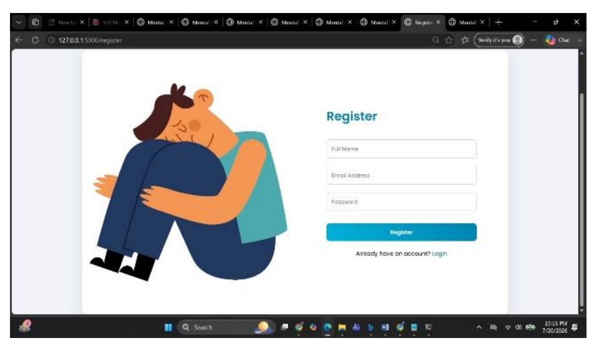
SYSTEM ARCHITECTURE:

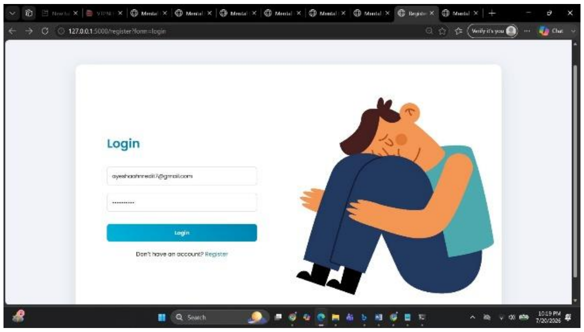


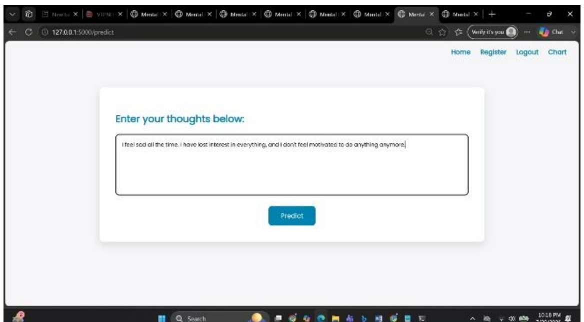


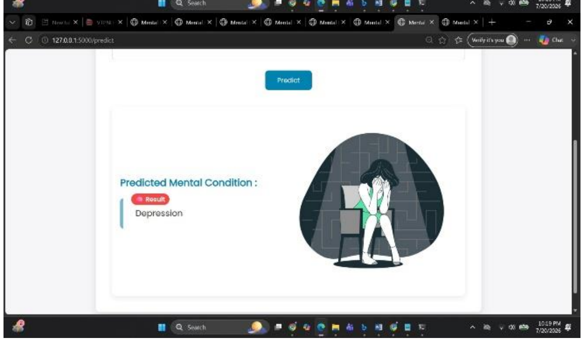
7.RESULTS:











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8. DISCUSSION AND CONCLUSION

The proposed project focuses on developing an intelligent system for multiclass mental illness prediction using social media text and advanced NLP techniques. The framework integrates MentalBERT and MelBERT for capturing mental health-specific contextual information and metaphorical expressions commonly used by individuals experiencing psychological distress. CNN layers are employed for extracting important semantic features, while BiLSTM networks capture sequential dependencies and contextual relationships within text data. Unlike traditional binary classification methods, the proposed system supports multiclass prediction of disorders such as depression, anxiety, PTSD, and bipolar disorder. The hybrid architecture improves prediction accuracy and contextual understanding, making the system a useful supportive tool for early mental health detection and digital healthcare applications.

Conclusion

This project presents a comprehensive deep learning-based framework for the prediction and classification of multiple mental health disorders using social media text. By leveraging advanced NLP techniques and domain-specific transformer models such as MentalBERT and MelBERT, the system effectively captures the subtle, emotional, and metaphorical nuances that are often present in online expressions of psychological distress. The integration of CNN and BiLSTM further enhances the model's ability to extract local features and understand the sequential flow of language, making it highly effective in identifying complex mental health patterns.

Through rigorous preprocessing, embedding, and evaluation strategies, the proposed system demonstrates superior performance over traditional models, offering improved accuracy, contextual understanding, and robustness. It successfully addresses the limitations of binary classification systems by supporting multiclass mental illness prediction, making it suitable for practical deployment in real-world mental health monitoring applications.

While the system shows promising results, there is room for future improvements, such as incorporating multimodal data, supporting multiple languages, adding explainability features, and deploying in a secure real-time application environment. Overall, this project highlights the transformative potential of artificial intelligence in supporting mental health awareness, early detection, and intervention, ultimately contributing to better mental well-being in society

9. FUTURE ENHANCEMENT

While the current system demonstrates strong performance in detecting and classifying multiple mental health conditions based on social media text, there remains significant scope for improvement and expansion. Future enhancements can focus on increasing the system's accuracy, interpretability, real-time usability, and inclusivity to broaden its impact and applicability. One key enhancement involves the integration of multimodal data. Currently, the system relies solely on textual input, but combining text with other modalities such as images, audio (voice recordings), and physiological signals (e.g., heart rate from wearables) could lead to more holistic and accurate mental health assessments. This multimodal approach would better mimic real-world diagnostics and capture behavioral patterns beyond language. Another area for enhancement is the implementation of explainable AI (XAI) techniques. By incorporating attention visualization or explainable layers, the system can highlight which parts of the input text contributed most to a given prediction. This would not only improve trust among users and clinicians but also provide deeper insights into the linguistic markers of specific mental disorders. Additionally, the system could be improved by supporting multilingual capabilities, enabling it to analyze mental health content written in languages other than English. This would make the tool more accessible to non-English-speaking populations and extend its usability globally. The deployment of the model into a real-time web or mobile application with privacy safeguards is another valuable enhancement. Such a platform could enable users to receive mental health insights and connect with professionals while ensuring data confidentiality and ethical usage. Finally, continual learning mechanisms could be incorporated so the model can adapt over time with new data, evolving slang, or emerging patterns of digital expression. This would keep the model up-to-date with linguistic and cultural changes in how mental health is discussed online.

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