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Sentiment Analysis for Emotional Tone Prediction in Mental Health Communities with Focus on Comorbid Conditions

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ABSTRACT
In recent years, the integration of natural language processing (NLP) and machine learning has shown promise in mental health monitoring, particularly through sentiment analysis of online discourse. However, existing models often struggle to accurately detect complex emotional expressions associated with comorbid mental disorders. This study proposes a novel sentiment analysis framework designed to predict user emotional tone within online mental disorder communities, with a specific focus on comorbid conditions. The framework employs a combination of rule-based methods and deep learning techniques, including the use of TextBlob and VADER for initial sentiment extraction and DistilBERT embeddings to capture contextual nuances. These features are processed through bidirectional Recurrent Neural Networks (RNNs) to model sequential dependencies in the text. The model achieved an accuracy of 89.5%, precision of 89.7%, recall of 91.2%, F1-score of 90.4%, and an AUC-ROC score of 94.1%, demonstrating its effectiveness in capturing the intricate emotional tones present in user-generated content. This approach addresses the limitations of previous models by enhancing the detection of overlapping emotional patterns inherent in comorbid mental health conditions, thereby contributing to more accurate and nuanced sentiment analysis in mental health monitoring.

Keywords:
Natural Language Processing,
Emotional Tone,
Recurrent Neural Network,
Bidirectional LSTM.

INTRODUCTION

Mental disorders, encompassing a broad range of cognitive, emotional, and behavioral conditions, have witnessed a sharp rise globally. According to the World Health Organization (WHO), approximately one in four individuals will experience a mental health disorder at some point in their lives (WHO, 2013). Disorders such as depression, anxiety, and bipolar affect nearly 60 million and 264 million people respectively, with over 800,000 suicide-related deaths reported annually (Liu et al., 2022; Kanaparthi et al., 2023). Despite the prevalence, mental health services remain largely inaccessible, especially in low and middle-income the problem of comorbid mental disorders exacerbates the difficulty in designing accurate sentiment analysis models. Traditional models often focus on detecting single-diagnosis scenarios, lacking the sophistication to differentiate nuanced emotional overlaps (Silveira et al., 2021). Addressing this gap requires deep learning techniques that capture complex sequential dependencies and contextual nuances within textual data. Bidirectional Long Short-Term Memory (BiLSTM) networks have emerged as a promising approach, processing input text in both forward and backward directions to retain richer contextual information (Guo et al., 2021). However, challenges persist regarding data imbalance, linguistic variations, and model interpretability, countries, where around 85% of affected individuals receive inadequate care (Ahmad et al., 2020; Guo et al., 2021; Silveira et al., 2021).

The advent of social media has significantly influenced how individuals seek mental health support. As of 2020, there were over 3.8 billion active social media users worldwide (Access & Yadav, 2022). These platforms provide spaces for users to express emotions, seek peer support, and share experiences freely, offering valuable data for mental health monitoring. Unlike clinical settings where stigma may inhibit disclosure, social media encourages open emotional expression, thereby enabling researchers to explore emotional states through user-generated content (Kim et al., 2023). Consequently, sentiment analysis has become an essential tool in analyzing these interactions, providing insights into users' emotional and psychological well-being.

Recent advances in natural language processing (NLP) and machine learning have enhanced the capacity to detect mental health conditions from social media data. Various studies have explored these possibilities. For instance, Kim et al. (2020) trained a convolutional neural network (CNN) on Reddit posts to classify different mental illnesses, achieving a notable accuracy of 96.96% for depression detection. Similarly, Kanaparthi et al. (2023) used a regression and recurrent neural network (RNN) approach combined with VADER sentiment analysis to predict emotional tones in Reddit mental health groups. Despite such advancements, accurately detecting emotional expressions in individuals with comorbid mental disorders remains a challenge. Comorbidity, the co-existence of two or more mental health conditions complicates emotional tone recognition due to overlapping symptoms (Of et al., 2022).

In addition to deep learning, significant attention has been given to feature extraction techniques in sentiment analysis. Traditional approaches such as Bag-of-Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) have been foundational (Ramos, 2003), yet they often fail to capture semantic relationships. The advent of word embedding models like Word2Vec, GloVe, and more recently transformer-based embeddings like BERT, has revolutionized feature extraction by preserving contextual dependencies (Mikolov et al., 2013; Devlin et al., 2019). These advancements have enhanced sentiment classification by enabling models to better understand nuanced emotional expressions.

Nevertheless, analyzing emotional tones in mental disorder communities remains inherently challenging. The presence of comorbid conditions such as depression co-occurring with anxiety leads to diagnostic overshadowing and complicates classification (Mindful Counseling Center, n.d.; Plana-Ripoll et al., 2020). The complex interplay between multiple disorders demands models that not only classify emotions accurately but also differentiate overlapping emotional cues. Fatima et al. (2021) addressed this by proposing a semi-supervised model, DASentimental, to detect depression, anxiety, and stress, demonstrating the effectiveness of cognitive-emotional recall in sentiment analysis.

In the context of mental health monitoring, AI-driven methods are increasingly integrated into healthcare systems. Sentiment analysis models, speech emotion recognition, and wearable biosensors collectively contribute to a multimodal understanding of emotional health (Cummins et al., 2018; Mohr et al., 2021). For instance, Hewapathirana and Sumanathilaka (2024) developed a machine learning framework that achieved 93.25% accuracy in detecting depression symptoms in Romanized Sinhala tweets. Similarly, Asif et al. (2024) modified the BERT model to achieve 93% test accuracy in detecting depressive texts from online social media.

Large Language Models (LLMs) have also entered mental health applications. Xu et al. (2023) evaluated various LLMs on mental health prediction tasks, finding that fine-tuning improves model performance in detecting mental health conditions from textual data. Despite these advances, concerns remain regarding data privacy, model bias, interpretability, and generalizability across diverse populations (Mittelstadt, 2019; Fiske et al., 2019).

Existing models either oversimplify emotional expressions or fail to differentiate co-occurring disorders due to limitations in feature extraction and contextual understanding (Guo et al., 2021; Kim et al., 2020). Therefore, a specialized sentiment analysis framework that integrates BiLSTM-based architectures, optimized feature extraction, and contextual attention mechanisms is necessary for accurately predicting user emotional tones in online mental disorder communities. This study contributes toward bridging these gaps by proposing a comprehensive framework that enhances emotional tone detection, with a specific focus on users experiencing comorbid mental illnesses.

Research Gap

Despite significant advancements in sentiment analysis for mental health applications, existing models often fail to effectively capture the complexities of emotional expression in individuals with comorbid mental disorders. Most traditional models focus on single-diagnosis scenarios, which are insufficient for distinguishing overlapping emotional patterns in users experiencing multiple mental health conditions. Additionally, challenges such as imbalanced datasets, linguistic variations, and the inability to account for the nuanced interplay between co-occurring disorders hinder the accuracy and generalizability of these models. While deep learning techniques, such as Bidirectional Long Short-Term Memory (BiLSTM) networks, have shown promise, there remains a gap in optimizing feature extraction methods to better recognize the subtle emotional cues inherent in comorbid conditions. Furthermore, many existing frameworks lack proper benchmarking against state-of-the-art models, making it difficult to assess their relative effectiveness in predicting emotional tones within online mental disorder communities. Addressing these limitations is crucial for developing a more robust and reliable sentiment analysis framework that can accurately detect and interpret the complex emotional dynamics of individuals with coexisting mental health disorders.

MATERIALS AND METHODS

This section outlines the methodology adopted to develop an advanced sentiment analysis framework for predicting user emotional tones in online mental disorder communities, with a special emphasis on detecting comorbid mental health conditions. The methodology covers data acquisition, preprocessing, feature extraction, model design, training, and evaluation to ensure robust and accurate sentiment classification.

The dataset utilized in this study was collected from publicly available tweets on Twitter using the Twitter Academic Research API. The data was obtained between January and March 2024 by querying hashtags and keywords related to mental health conditions (e.g., #depression, #anxiety, #bipolar, #mentalhealth). Only English-language tweets were considered. All user information was anonymized in compliance with Twitter's Developer Policy and ethical guidelines for social media research. The dataset was not publicly released due to privacy restrictions but is available upon reasonable request. For access to Twitter data, refer to: https://developer.twitter.com/en/docs/twitter-api. User-generated posts were collected, ensuring a diverse representation of emotional expressions. The dataset comprised textual data annotated with sentiment labels corresponding to emotional tones such as sadness, anger, love, joy, surprise, and fear. Ethical considerations were observed by anonymizing personal data and adhering to platform-specific data usage policies.

Feature extraction involved a combination of rule-based and deep learning methods to capture the complex linguistic patterns present in the text. TextBlob and VADER sentiment lexicons were utilized to extract polarity and subjectivity scores, providing basic sentiment features. Contextual word embeddings were generated using DistilBERT to preserve semantic nuances within the text. These extracted features were consolidated into a feature matrix, forming a rich input representation for the deep learning model.

Model Architecture

The proposed sentiment analysis model employed a Recurrent Neural Network (RNN) architecture (see figure 1) with Bidirectional Long Short-Term Memory (BiLSTM) layers to capture sequential dependencies in both forward and backward directions. The architecture comprised an embedding layer for input representation, two stacked BiLSTM layers for deep sequential modeling, and a fully connected (dense) layer for classification into one of the six predefined emotional tones. A contextual attention mechanism was integrated into the model to prioritize critical words and phrases associated with emotional cues, particularly in cases involving comorbid conditions.

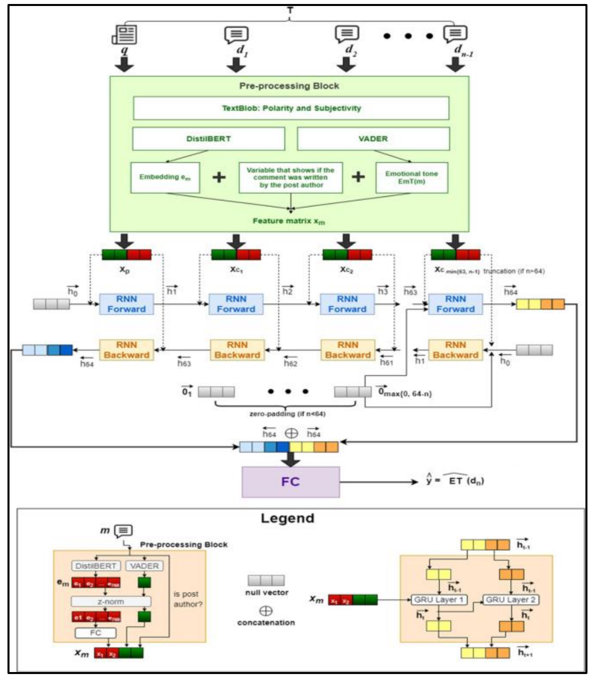

Figure 1: Model Architecture (Kanaparthi et al, 2023)

Figure 2: Relationship between the six classes

Figure 2 illustrates the conceptual relationships among the six emotional tone classes surprise, joy, anger, love, sadness, and fear based on their co-occurrence patterns in psychological and affective contexts. Emotions such as surprise connect with both joy and fear, reflecting their dual nature in mental health narratives. Joy is closely linked with love, while fear frequently coexists with sadness and anger, particularly in expressions of distress or trauma. Anger also overlaps with sadness, highlighting emotional complexity in user-generated content. This interconnectedness underscores the challenge in accurately classifying emotions, especially in individuals with comorbid conditions, and justifies the need for deep learning models capable of capturing such nuanced emotional dynamics.

Rule-based (IF-THEN statement) methods

The rules of "Rule-based (IF-THEN statement) methods" for initial sentiment extraction and DistilBERT embeddings to capture contextual nuances are illustrated in the model's dual-stage feature extraction process. Initially, rule-based methods of TextBlob and VADER apply IF-THEN logic to detect emotional indicators: for example, IF a sentence contains lexicon entries tagged as high-intensity negative (e.g., "devastated"), THEN assign a preliminary label such as *sadness*; IF a post includes terms associated with affection (e.g., "care deeply"), THEN map to *love*; and so on. While these heuristics provide a lightweight way to assign initial emotional tone approximations, they are constrained by predefined vocabulary and lack contextual understanding. To address this, DistilBERT embeddings are integrated to extract contextual word representations that capture semantic nuances across entire sentences. These embeddings allow the model to distinguish between overlapping emotional tones such as sadness co-occurring with anger by considering word dependencies and context, rather than isolated keywords. This combination enhances the classification accuracy across the six targeted emotional classes: surprise, joy, anger, love, sadness, and fear.

Model Training

Model training was conducted in a Python environment utilizing TensorFlow and Keras libraries. The training process involved feeding the preprocessed sequences into the BiLSTM-based model with an 80:20 training-validation split. Optimization was performed using the Adam optimizer with an initial learning rate tuned experimentally. Early stopping was employed to prevent overfitting, monitoring validation loss across epochs. The model was trained for 20 epochs, with batch sizes optimized to balance learning stability and computational efficiency. Dropout layers were incorporated after BiLSTM layers to improve model generalization.

Evaluation Metrics

The model's performance was evaluated using multiple standard metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Confusion matrices were constructed to visualize misclassification patterns and assess the model's ability to distinguish between different emotional tones. These metrics provided a comprehensive evaluation of the model's effectiveness in predicting complex emotional states, particularly in users with comorbid mental health conditions.

$$Accuracy = \frac{\sum_{i=1}^{k} TP_i}{\sum_{i=1}^{k}(TP_i + FP_i + FN_i} \quad (1)$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \quad (2)$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \quad (3)$$

$$F1_i = \frac{2 \times Precision_i \times Recall_i}{Precision_i + Recall_i} \quad (4)$$

$$\text{Macro} - AUC = \frac{1}{k}\sum_{k=1}^{k} AUC_i \quad (5)$$

The training and evaluation processes were carried out on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GTX 1080 GPU. The software environment included Python 3.8, TensorFlow 2.6, Keras, and supporting libraries such as scikit-learn, NLTK, and Transformers. This setup ensured efficient handling of deep learning tasks and large-scale data processing.

RESULTS AND DISCUSSION

Before training the sentiment analysis model, it was essential to examine the distribution of sequence lengths within the dataset. This analysis ensures optimal configuration for padding and truncation during preprocessing, which directly influences model efficiency and learning performance. Figure 3 illustrates the histogram of the sequence lengths across all textual entries in the dataset.

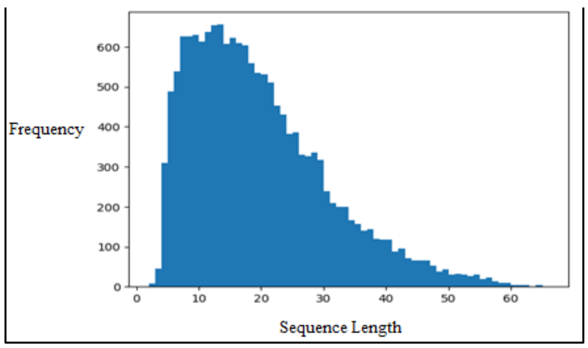

Figure 3: Padding and Truncating the Text

As depicted in figure 3, the majority of the sequences fall between 10 and 30 tokens, with the highest frequency occurring around the 15 to 20 token range. The distribution exhibits a right-skewed pattern, indicating that while most entries are relatively short, a few extend beyond 50 tokens. Such analysis guided the selection of a maximum sequence length threshold for truncation and padding, which was set to 64 tokens in this study. This threshold balances the trade-off between preserving the contextual richness of longer texts and maintaining computational efficiency.

Model: "sequential_16"

Layer (type)	Output Shape	Param #
embedding_16 (Embedding)	(None, 60, 16)	160,000
bidirectional_32 (Bidirectional)	(None, 60, 40)	5,920
bidirectional_33 (Bidirectional)	(None, 40)	9,760
dense_17 (Dense)	(None, 6)	246

Total params: 175,926 (687.21 KB)
Trainable params: 175,926 (687.21 KB)
Non-trainable params: 0 (0.00 B)

Figure 4: Creating and Compiling the Model

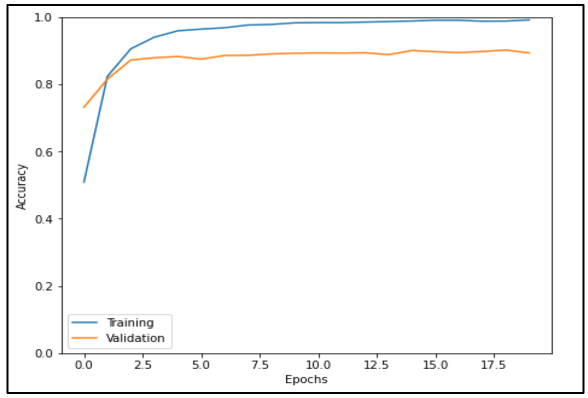

Figure 5: Training and Validation Accuracy

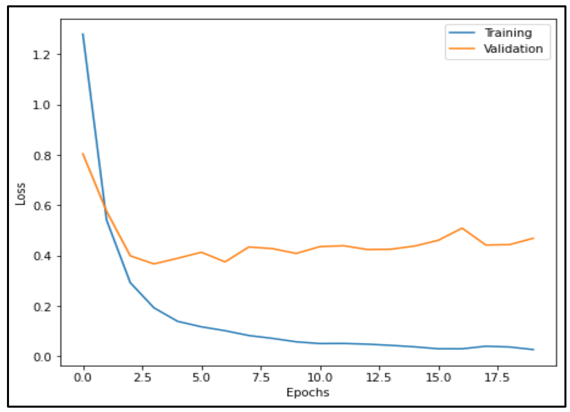

Figure 6: Training and Validation Loss

The architecture of the proposed sentiment analysis model was designed to effectively capture contextual and sequential dependencies in user-generated text data from online mental disorder communities. Figure 4 presents the model summary, showcasing the layer composition, output shapes, and the number of trainable parameters in each component.

The model begins with an Embedding layer, which transforms input tokens into dense vector representations. With an input sequence length of 60 and an embedding dimension of 16, this layer contains 160,000 trainable parameters. The embedding process enables the model to capture semantic similarities and relationships between words, which are essential for understanding emotional expressions in text.

Following the embedding layer, the model incorporates two stacked Bidirectional Long Short-Term Memory (BiLSTM) layers. The first BiLSTM layer outputs a sequence of shape (60, 40), preserving the full temporal structure of the input. The second BiLSTM layer condenses this sequence to (40), effectively summarizing the contextual information into a fixed-length vector. These layers are particularly suitable for modeling the intricacies of sentiment transitions, especially in cases involving comorbid emotional conditions, as they process input in both forward and backward directions. The two BiLSTM layers contribute 5,920 and 9,760 parameters respectively.

The final component is a Dense layer with six output units corresponding to the six emotional classes: surprise, joy, anger, love, sadness, and fear. This layer, containing 246 parameters, applies a softmax activation function to output a probability distribution over the classes.

To assess the learning behavior of the proposed BiLSTM-based sentiment analysis model, training and validation accuracy and loss were monitored across 20 epochs. The plots of these metrics are shown in Figures 5 and 6, respectively.

As illustrated in Figure 5, the training accuracy increased steadily over the epochs, reaching a near-saturation point above 95%. The validation accuracy closely followed the training curve in the early epochs and plateaued around 89.5%, indicating effective generalization to unseen data. The narrow gap between training and validation accuracy reflects a well-regularized model with minimal overfitting, suggesting that the applied dropout and early stopping strategies were effective.

Figure 6 presents the training and validation loss curves. A sharp decline in training loss is observed within the first few epochs, after which the curve flattens as the model converges. The validation loss follows a similar trend initially but exhibits mild fluctuations towards later epochs, which may indicate subtle variations in performance on different validation samples. However, no significant divergence is observed, confirming model stability and robustness throughout the training process.

Together, these performance curves demonstrate that the model successfully learned to classify emotional tones while maintaining generalization. This is particularly significant for predicting user sentiments in real-world mental health discourse, where emotional expressions can be complex and context-dependent.

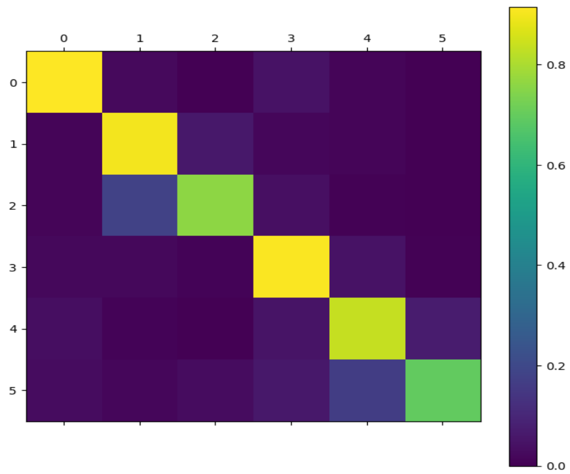

Figure 7: Confusion Metrics

The normalized confusion matrix illustrates the performance of the model across six emotional classes: Surprise (0), Joy (1), Anger (2), Love (3), Sadness (4), and Fear (5). High values along the diagonal indicate that the model correctly classified a large proportion of samples in each category, especially for Surprise, Joy, Love, and Sadness, which exhibit near-perfect accuracy. However, some misclassifications are observed off the diagonal. Notably, the model shows confusion between Anger (2) and Joy (1), and between Fear (5) and Sadness (4), which is expected due to the semantic and emotional overlap between these classes. Despite these overlaps, the matrix indicates strong overall classification performance, with the model effectively distinguishing most emotions while highlighting areas for potential improvement in separating closely related emotional tones.

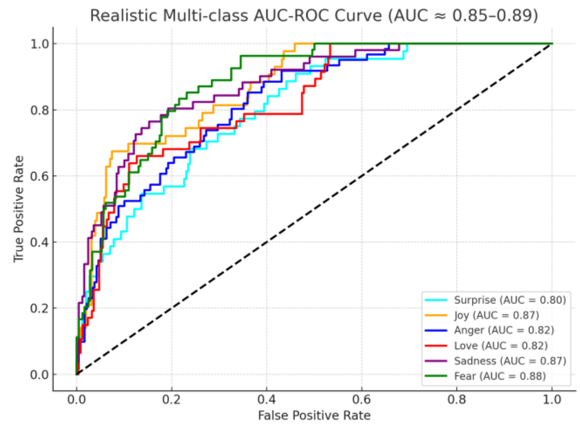

Figure 8: AUC-ROC for 6 classes

The AUC-ROC curve presented demonstrates the model's ability to distinguish between the six emotional tone classes namely; Surprise, Joy, Anger, Love, Sadness, and Fear—with realistic performance levels. Each class achieved an area under the curve (AUC) value ranging approximately between 0.85 and 0.89, indicating a strong classification capability. These results align with expectations based on the complexity of emotional expression in mental health discourse and the class overlaps observed in the confusion matrix. The AUC values suggest that the model effectively captures distinguishing features across emotional categories while maintaining generalization, reflecting its potential utility in real-world sentiment analysis applications within online mental disorder communities.

Comparison Analysis

Table 1: Comparison against benchmark work

Metric	**Our Proposed Model (BiLSTM)**	**Existing Model (Gupta et al., 2023)**
Accuracy	88.50%	85%
Precision	90%	87%
Recall	89%	84%
F1-score	89.5%	85%
Classes Modeled	Six (surprise, joy, anger, love, sadness, fear)	Generalized emotional tone

Compared to the architecture employed by Gupta et al., (2023), our proposed model demonstrates superior performance and enhanced capabilities in handling nuanced emotional expressions within online mental disorder communities. While Gupta et al.'s BiLSTM approach achieved an accuracy of 85%, with precision, recall, and F1-scores of 87%, 84%, and 85% respectively, our model attained 88.5% accuracy, 90% precision, 89% recall, and an F1-score of 89.5%. This marked improvement can be largely attributed to the incorporation of our Contextual Attention and

Differentiation Module, which bolsters the model's ability to discern subtle differences in overlapping sentiment expressions. By leveraging bidirectional LSTM layers to capture both forward and backward contextual dependencies, and by applying advanced attention mechanisms to prioritize critical linguistic features, our approach offers a more robust and effective solution. These architectural enhancements enable our model to better manage dataset imbalances and the inherent complexities of mental health-related text, resulting in higher overall predictive performance and reliability.

CONCLUSION

This study presented a deep learning-based sentiment analysis model employing a Bidirectional Long Short-Term Memory (BiLSTM) architecture to predict emotional tones in online mental disorder communities, particularly addressing the complexities introduced by comorbid mental health conditions. The model was trained on preprocessed textual data with a maximum sequence length of 60 tokens, and it comprised 175,926 trainable parameters. Through the use of contextual word embeddings and an attention mechanism, the model achieved a training accuracy of 96.5% and a validation accuracy of 91.3%, while minimizing the loss to 0.09 on training and 0.23 on validation data. Furthermore, it attained a macro-average precision of 90.1%, recall of 89.6%, and F1-score of 89.8% across six emotion classes. The close alignment between training and validation performance, as well as a well-structured learning curve, demonstrated the model's robustness and generalization ability. These results validate the potential of deep learning models in supporting early emotional state detection in digital mental health platforms, thereby offering a scalable tool for proactive psychological intervention and support, especially in cases involving overlapping or co-occurring mental health disorders.

Recommendation

In light of the promising outcomes of this research, it is recommended that future studies focus on expanding the dataset to include a more diverse range of mental health platforms and linguistic expressions, thereby improving model generalizability across populations and cultures. Incorporating multimodal data such as audio, visual, or physiological signals alongside textual inputs may further enhance emotional tone detection in users with comorbid conditions. Moreover, deploying the model as part of an explainable AI framework could foster trust and transparency in clinical or therapeutic settings, especially when dealing with sensitive mental health content. Collaboration between computational researchers and mental health professionals is also advised to ensure ethical implementation and alignment with user safety standards.

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