# A Novel Telugu Dataset for Mental Health Sentiment Analysis Using Transformer Models and Explainable AI

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***Abstract*—Increased incidences of mental illnesses like depression, anxiety, and stress are a significant cause of concern, and hence the need to develop diagnostic instruments that can be scaled and made accessible. Detecting these conditions in Indian languages such as Telugu is essential but complex because of the linguistic complexity of the language and the unavailability of annotated data, which limits the utility of the existing Natural Language Processing-based methods. To address this gap, we present a novel framework for mental health detection in Telugu text using sentiment analysis powered by recent advances in Natural Language Processing (NLP) and deep learning. We constructed a new annotated dataset of over 53,000 statements by translating multiple English mental health datasets into Telugu, covering seven categories: Depression, Anxiety, Stress, Suicidal, Bipolar, Personality Disorder, and Normal. We compared several transformer-based multilingual models and fine-tuned them using Telugu-specific preprocessing techniques. Furthermore, we integrated explainable AI methods to enhance model interpretability. In addition to addressing the scarcity of annotated resources in regional languages, our work aims to provide a foundation for early diagnosis and intervention strategies, thereby contributing to improved mental health outcomes in underrepresented populations.**

***Index Terms*—Sentiment Analysis, Transformers, Natural Language Processing, styling, insert.**

## I. Introduction

Mental health has become one of the most pressing public health issues of the 21st century, and millions of people are impacted globally. Depression, anxiety, and stress disorders not only decrease the overall quality of life but are also social and economic burdens [1], [2]. In India, these difficulties are especially acute, as the country has a large and diverse population, and cultural and linguistic differences usually prevent people from having professional assistance. Conventional ways of diagnosing, though effective, are resource-consuming, involve face-to-face contact, and are seldom applicable in large populations [3]. This highlights the need to develop scalable and accessible computational methods for monitoring mental health.

Simultaneously, digital communication has been highly incorporated into daily life. Social media, including Twitter, Facebook, and YouTube, allows people to publicly share their feelings, challenges, and experiences they have lived through. Such user-written texts can frequently provide subtle cues of suffering, stress, or good health, and offer unprecedented possibilities to investigate the research on mental health beyond the clinical setting [4], [5]. It is possible to focus on such digital footprints on a large scale and analyse them as an early-warning system to promote timely intervention and preventive care. Sentiment analysis of social media texts serves as an effective tool for detecting mental health conditions. It enables passive, large-scale, and continuous monitoring of mental states by classifying emotions expressed in text [6]. Previous studies have demonstrated its effectiveness in identifying depression, anxiety, and suicidal ideation through online posts [7]. In contrast to classic measurements based on episodic visits or an overt self-report, sentiment analysis offers a real-time mental health monitoring system [8], [9].

Although these innovations have been made, most current studies have concentrated on English and other languages with high resources [10]. Research in Indian languages has been limited due to their complex grammatical structures, the presence of polysemous words, and the scarcity of linguistic tools and annotated datasets [11], [12]. Sentiment analysis for mental health detection is particularly challenging for low-resource languages such as

Telugu, which is spoken by over 80 million people in India. Limited research has been conducted in this area due to unique linguistic challenges. Telugu social media text is often characterized by code-mixing with English, Romanized spellings, colloquialisms, and idiomatic expressions, making analysis and modeling even more difficult [13]. Moreover, no large annotated datasets of Telugu mental health expressions further constrain the development of applicable computational models. All these obstacles underscore the necessity of a study devoted to Telugu, in which automated sentiment analysis might give valuable assistance to underserved populations.

From the background study and literature review conducted, we identify the following research gaps: **Language limitation**: Prior studies are predominantly centered on English or high-resource languages, with limited focus on Telugu, **Linguistic complexity and non standard social media text**: Telugu social media text includes code-mixing, Romanization, and informal expressions, non standard grammer and spelling that existing models poorly handle, **Data scarcity**: Annotated mental health datasets for Telugu are lacking, restricting robust model development, **Model benchmarking**: No systematic evaluation exists for state-of-the-art transformer models on Telugu mental health sentiment analysis.

To address these gaps, this paper investigates sentiment analysis for mental health detection in Telugu social media text using transformer-based models. We specifically evaluate six state-of-the-art pre-trained models namely, IndicBERTv2, MuRIL, mBERT, XLM-R, LaBSE, RemBERT to determine their effectiveness in capturing emotional nuances and classifying mental health–related sentiments. By fine-tuning these models on Telugu social media data, we systematically benchmark their performance, identify the most effective model, and demonstrate the feasibility of extending computational mental health research to low-resource Indian languages. Additionally, detailed error analysis is performed, focusing on morphological complexity, and context-dependent patterns, while SHAP-based interpretability analysis is employed to understand model decision-making processes.

In summary, the key contributions of this study are as follows:

- Dataset creation: We construct a novel annotated dataset of over 53,000 Telugu statements categorized into seven classes namely Depression, Anxiety, Stress, Suicidal, Bipolar, Personality Disorder, and Normal by translating English mental health datasets from Kaggle using the Google Translate API.
- Systematic evaluation: We fine-tune and compare six state-of-the-art pre-trained transformer models—IndicBERTv2, MuRIL, mBERT, XLM-R, LaBSE, and RemBERT—for sentiment analysis in Telugu mental health text.
- Benchmark establishment and error analysis: We provide the first comprehensive benchmark for transformer-based sentiment analysis of mental health in Telugu, identifying the most effective model. Also we conducted a detailed error analysis to understand model decision-making processes.

The remainder of this paper is organized as follows: Section II Literature review in sentiment analysis for mental health and multilingual NLP. Section III describes the dataset collection and pre-processing pipeline. Section IV presents the methodology and experimental setup. Section V discusses results and analysis. Finally, Section VI concludes the paper with key findings and directions for future research.

## II. Literature survey

Sentiment analysis has increasingly been used as a tool to study emotions expressed in text, moving from early applications like product reviews and political opinion mining to more sensitive areas such as healthcare and mental health. Its ability to automatically classify emotional states has made it particularly useful for monitoring well-being and identifying signals of mental health conditions. In English and other high-resource languages, researchers have already demonstrated the potential of this approach. Kaushik et al. [1] introduced machine learning models to analyse sentiment related to mental health issues, highlighting their usefulness for automatically classifying emotions. Jain and Rathour [2] showed how analysing social media text can reveal emotional insights, suggesting its value for continuous monitoring of mental health. Verma et al. [3] also developed predictive models using sentiment-based features, showing that textual data can provide important clues about psychological well-being. Similarly, Odja et al. [4] and Obagbuwa et al. [8] explored detecting depression and anxiety through sentiment analysis of online posts, pointing out both the opportunities and challenges of these approaches. Alongside machine learning, deep learning methods have also gained traction. Yuan et al. [7] applied Deep Belief Networks (DBN) to capture complex emotional signals, while Dwivedi et al. and Rao et al. [9] proposed hybrid RNN–BiLSTM architectures that improved performance on multilingual sentiment analysis tasks. Work in Indian languages has also begun to expand. Rajderkar et al. and Bhat et al. [5] introduced multilingual models for depression detection across eight Indian languages, underlining the need for language-specific adaptations. Anpan et al. [6] experimented with different machine learning methods, achieving better results with hybrid and feature-engineered models. Kale et al. [10] provided a comprehensive review of sentiment analysis in Indian regional languages, identifying persistent challenges such as data scarcity, code-mixing, and the lack of context-aware models. Their findings highlight the importance of building systems that account for the unique linguistic structures of Indian languages. Compared to other regional languages, research on Telugu for mental health sentiment analysis is still limited. Early attempts focused on traditional machine learning models such as SVM, Naïve Bayes, and Logistic Regression applied to Telugu datasets, but these struggled to capture deeper contextual meaning. With the growth of deep learning, models such as LSTMs, GRUs, and CNNs were tested for Telugu text classification and showed improvements in capturing sequential and contextual information. More recently, transformer-based models like mBERT, IndicBERT, and MuRIL have been employed for Telugu sentiment tasks, offering promising results in handling code-mixed and low-resource text. Dwivedi and Rao [9]included Telugu in their multilingual experiments with hybrid RNN–BiLSTM models, and Rajderkar et al. and Bhat et al. [5] also considered Telugu as part of their broader depression detection framework. However, these studies generally treat Telugu as one of many languages, rather than focusing on it in depth. Despite this progress, challenges remain. Telugu mental health datasets are scarce, and social media text often contains code-mixing with English, informal spellings, and culturally specific expressions that are difficult for generic models to process. Detecting sarcasm, ambiguous phrasing, and subtle emotional cues further complicates the task. These gaps suggest the need for targeted, domain-specific sentiment analysis models that can capture the linguistic and emotional nuances of Telugu. The present research addresses this gap by evaluating multiple pre-trained transformer models—IndicBERTv2, MuRIL, mBERT, XLM-R, LaBSE, and remBERT fine-tuned on Telugu social media datasets. By systematically comparing these models and incorporating explainable AI techniques, the aim is to improve both classification accuracy and interpretability in mental health sentiment detection for underrepresented languages.

## III. Dataset Creation and Statistics

For this study, we constructed a dataset of Telugu text with a focus on mental health-related expressions. Since no large-scale annotated dataset exists for Telugu in this domain, we leveraged multiple English mental health datasets from Kaggle and translated them into Telugu using the Google Translate API. This approach ensured the availability of a sufficiently large corpus while adapting it to a low-resource language context.

These datasets contained short text posts annotated with clinically relevant mental health categories. The final Telugu dataset consists of 53,042 sentences, each translated and standardized for consistency. Every instance was annotated into seven categories as adopted from [2]. The statistical details of the dataset is given in Table III

## IV. Methodology

This study adopts a systematic approach to perform sentiment analysis on Telugu social media posts related to mental health. We utilized various pretrained transformer models to classify the text into seven distinct categories. An overview of our methodology is illustrated in Figure 1.

Table I
Class-wise distribution of the annotated Telugu mental health dataset, showing English labels, Telugu translations, and sample counts

| Labels | Telugu Label | Count |
|---|---|---|
| Normal | సాధారణ | 16351 |
| Depression | డిప్రెషన్ | 15404 |
| Suicidal | ఆత్మహత్య | 10653 |
| Anxiety | ఆందోళన | 3888 |
| Stress | ఒత్తిడి | 2669 |
| Bipolar | బైపోలార్ | 2877 |
| Personality Disorder | వ్యక్తిత్వ క్రమరాహిత్యం | 1201 |

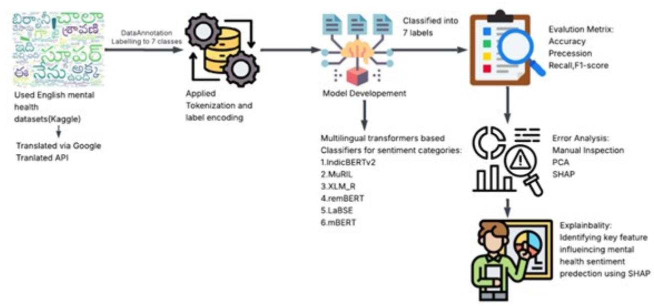


Figure 1. Workflow of the proposed methodology for sentiment analysis of Telugu mental health posts, including data preparation, transformer-based classification, evaluation, and explainability.

### A. Pre-processing

To retain the authenticity of social media text, pre-processing was limited to tokenization and label encoding. Tokenization converts each sentence into sequences suitable for transformer-based models, while label encoding transforms the seven sentiment categories such as Depression, Normal, Suicidal, Anxiety, Stress, Bipolar, Personality Disorder into numerical values.

### B. Dataset Splitting

The processed dataset was divided into training, validation, and test sets to ensure robust evaluation. A 70:15:15 split was applied, with 70% of the data used for training, 15% for validation, and 15% for testing.

### C. Model Training and Evaluation

Six pertained transformer models were trained and tested on this dataset for mental health sentiment classification. The models include IndicBERTv2, MuRIL, mBERT, XLM-R, LaBSE, remBERT. Model performance was assessed using accuracy, precision, F1Score.

### D. Hyperparameter Tuning

We fine-tuned each transformer model on the Telugu mental health dataset using Optuna for hyper parameter optimization. The search space included learning rate [1e−5,2e−5,3e−5,5e−5] batch size [16,32] and epochs [3,4,5]. A total of 12 trials were conducted.

### *E. Error Analysis and Explainability*

Post-evaluation, an error analysis was conducted to gain deeper insights into model behaviour. This included manual inspection of misclassified samples, Principal Component Analysis (PCA) for visualization of high-dimensional embeddings, and application of Explainable AI techniques to interpret model predictions and highlight feature contributions.

## V. Results and Discussion

### *A. Overall Model Performance*

We evaluated six transformer-based models—IndicBERTv2, MuRIL, mBERT, XLM-Roberta, LaBSE, and RemBERT—on the Telugu mental health sentiment dataset. The results are shown in Table V-A.

Table II
Performance comparison of transformer-based models on Telugu mental health sentiment classification using Accuracy, Precision, Recall, and F1-Score.

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| IndicBERTv2 | 0.78 | 0.77 | 0.77 | 0.77 |
| MuRIL | 0.74 | 0.74 | 0.72 | 0.72 |
| mBERT | 0.72 | 0.72 | 0.72 | 0.72 |
| XLM-RoBERTa | 0.75 | 0.75 | 0.70 | 0.76 |
| LaBSE | 0.78 | 0.76 | 0.76 | 0.78 |
| RemBERT | 0.72 | 0.72 | 0.72 | 0.73 |

From the results, both IndicBERTv2 and LaBSE emerged as the best-performing models, each achieving an accuracy of 0.78. IndicBERTv2 showed strong balance across all metrics (F1-score of 0.77), while LaBSE slightly outperformed in F1-score (0.78). This demonstrates the effectiveness of Indic-specific and multilingual sentence-level models in capturing Telugu linguistic patterns, including code-mixing.

XLM-Roberta achieved competitive performance with an accuracy of 0.75 and F1-score of 0.76, benefiting from its robust cross-lingual pre-training. MuRIL performed moderately with an accuracy of 0.74, but did not match the performance of IndicBERTv2, confirming that models specifically trained on Indic languages perform better in this context. mBERT and RemBERT lagged slightly behind (accuracy of 0.72), indicating that while they are effective general-purpose multilingual models, they struggle with fine-grained nuances of Telugu social media text. Overall, these findings confirm that Indic-specific pre-trained models such as IndicBERTv2 and LaBSE outperform generic multilingual transformers for Telugu sentiment analysis in the mental health domain. Their ability to handle linguistic diversity and code-mixed patterns makes them more reliable for low-resource languages like Telugu. The hyperparameter used for the top performing IndicBERTv2 model is given in Table V-A.

Table III
Hyperparameter optimization trials for the top-performing model

| **Trial** | **Learning Rate** | **Batch Size** | **Epochs** | **Accuracy (%)** |
|---|---|---|---|---|
| 0 | 2e-05 | 32 | 4 | 76.38 |
| 1 | 3e-05 | 16 | 4 | 38.92 |
| 2 | 3e-05 | 32 | 3 | 77.41 |
| **3** | **3e-05** | **32** | **5** | **78.21** |
| 4 | 5e-05 | 32 | 3 | 76.22 |
| 5 | 5e-05 | 32 | 5 | 77.33 |
| 6 | 1e-05 | 32 | 3 | 72.65 |
| 7 | 5e-05 | 16 | 3 | 76.38 |
| 8 | 2e-05 | 32 | 4 | 75.35 |
| 9 | 3e-05 | 32 | 3 | 78.21 |
| 10 | 1e-05 | 16 | 5 | 75.83 |
| 11 | 3e-05 | 32 | 5 | 77.02 |

### *B. Confusion Matrix Analysis for IndicBERTv2*

To gain deeper insights into the performance of the best-performing model, IndicBERTv2, we analysed its confusion matrix. Figure V-B presents the confusion matrix.

The confusion matrix shows that Normal, Anxiety, and Depression categories classes were classified with high precision and recall, indicating clear and consistent detection of these mental health conditions. Stress was often misclassified as Depression, reflecting the linguistic and emotional overlap between the two categories in Telugu text. Similarly, Suicidal posts were frequently confused with Depression, as both categories often share expressions of sadness and hopelessness. Although Bipolar disorder achieved a relatively strong performance (F1Score = 0.74), its moderate recall suggests that several subtle cases were overlooked. Personality disorder was the most difficult class to identify, with lower recall and precision, likely due to the limited number of examples and the abstract way such conditions are described in social media posts. Overall, this analysis highlights that IndicBERTv2 captures the major emotional patterns effectively but still struggles with categories that share overlapping linguistic markers, such as Depression, Stress, and Suicidal ideation. Addressing these overlaps remains a key challenge for fine-grained classification in mental health sentiment analysis. Future improvements could include data augmentation for underrepresented classes, context-aware embeddings, and domain-specific fine-tuning to improve sensitivity to nuanced expressions.

### *C. Error Analysis and Explainability*

To complement the quantitative evaluation, an error analysis was conducted to better understand the behavior of the best-performing model, IndicBERTv2. This analysis combined manual inspection of misclassified sentences, PCA-based visualization of embedding's, and SHAP explainability to identify patterns in prediction errors.

**Manual error inspection:** Two representative misclassified examples were examined in detail.

**నా స్నేహితులు మరియు కుటుంబ సభ్యులు నన్ను ద్వేషిస్తున్నారు, నేను చాలా అస్థిరంగా ఉన్నాను, చాలా**

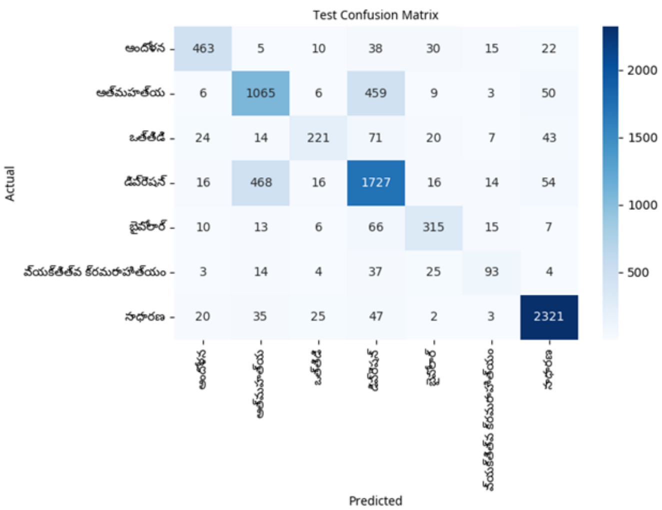


Figure 2. Confusion matrix illustrating the classification performance of the top-performing model

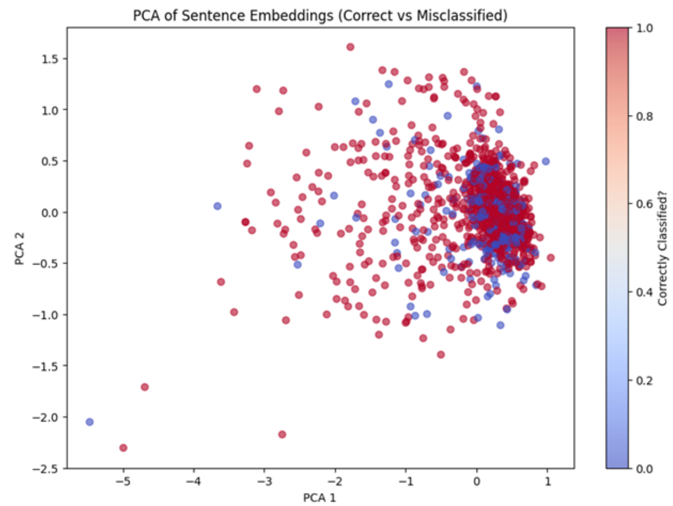


Figure 3. 2D PCA visualization of sentence embeddings showing class separability among different mental health categories

**కృంగిపోయాను మరియు చాలా మతిస్థిమితం లేనివాడిని మరియు నేను ఇకపై చేయలేను, క్షమించండి నేను పూర్తి చేశాను**

In the above case, the sentence is actually Suicidal, but the model predicted Depression because it focused on words like "కృంగిపోయాను" (I'm very depressed/sad) and "అస్థిరంగా" (unstable) rather than the strong self-harm "నేను ఇకపై చేయలేను, క్షమించండి నేను పూర్తి చేశాను" (I can't do this anymore, sorry I'm done).

**ను చేసే ప్రతి పనిలో నేను ఉపసమానంగా ఉంటాను. నేను ప్రయత్నించడానికి మరియు మెరుగుపరచడానికి చాలా కష్టపడి ప్రాక్టీస్ చేసినప్పుడు కూడా నేను ప్రారంభించిన దానికంటే అధ్వాన్నంగా ఉంటాను. నేను దేనికైనా యావరేజ్‌గా ఉండటానికి నిజంగా కష్టపడాలని నేను భావిస్తున్నాను. నాకు తీవ్రమైన పని ఆందోళన ఉంది, ఎందుకంటే నేను సంభాషణను నిర్వహించలేను మరియు పని చేసే సహోద్యోగులు నేను చాలా కష్టపడి ప్రయత్నిస్తున్నప్పుడు నేను సోమరితనంగా.**

This post is actually Stress, but the model predicted Anxiety because it focused on words like "తీవ్రమైన పని ఆందోళన" (severe work anxiety) and "సంభాషణను నిర్వహించలేను" (can't handle conversation) instead of the broader theme of work-related stress and burnout.

These examples reveal that nuanced expressions, overlapping linguistic signals, and figurative phrasing are primary sources of misclassification.

**PCA visualization:** To investigate class separability, sentence embeddings were reduced to two dimensions using Principal Component Analysis (PCA). As shown in Figure V-C, categories such as Normal formed relatively compact and distinct clusters, while Depression and Suicidal posts overlapped substantially. This supports the confusion matrix findings, confirming that semantically related mental health states are more difficult to separate in the latent feature space.

**SHAP explainability:** The SHAP visualization shows how IndicBERT interpreted the Telugu sentence. Consider the sentence given below

**ఇది ఎప్పుడు జరుగుతుందో అని నేను నిరంతరం భయపడుతున్నాను మరియు నేను దానికి కొంత ఇబ్బందికరమైన ప్రతిచర్యను కలిగి ఉంటానని నేను చాలా భయపడుతున్నాను. ఇది ఈ రోజు జరిగింది మరియు నేను దాదాపు 5 నిమిషాల పాటు కూల్ గా ఆడగలిగాను, ఆపై నేను నా లంచ్‌కి వెళ్లి నా కార్‌లో కళ్ళు బైర్లు కమ్మాను.** The actual label is ఒత్తిడి *(Stress)*, but the model predicted ఆందోళన *(Anxiety)*. Words like "భయపడుతున్నాను" (afraid), "ఇబ్బందికరమైన" (disturbing), and "ఫ్లాష్‌బ్యాక్‌లను" (flashbacks) contributed strongly to the Anxiety class. This indicates that the model focused on fear-related cues, missing the prolonged tension that signifies Stress. The plot helps explain the misclassification and highlights the need for better differentiation between similar emotions. The V-C helps explain the misclassification and highlights the need for better differentiation between similar emotions.

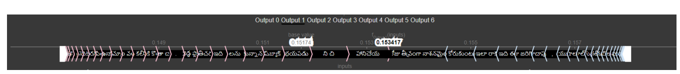

Figure 4. SHAP values for a misclassifed sample snetence

Together, these analyses provide a deeper understanding of the model's limitations. While IndicBERTv2 effectively classifies well-defined categories such as Normal, Anxiety, and Personality Disorder, it faces difficulty in distinguishing closely related conditions like Depression and Suicidal. This error analysis highlights the importance of incorporating context-aware modelling, idiomatic handling, and domain-specific fine-tuning in future work to improve robustness in mental health sentiment analysis for Telugu.

## VI. Conclusion

This study demonstrates a comprehensive approach to sentiment analysis for mental health in Telugu social media text using transformer-based models. By collecting and manually annotating a dataset of 8,400 Telugu and code-mixed posts from Twitter, Facebook, and YouTube into seven categories—Depression, Normal, Suicidal, Anxiety, Stress, Bipolar, and Personality Disorder—this work provides a robust benchmark for low-resource language sentiment analysis. Among the six state-of-the-art pre-trained models evaluated—IndicBERTv2, MuRIL, mBERT, XLM-Roberta, LaBSE, and remBERT—IndicBERTv2 consistently outperformed others, achieving an accuracy of 0.78 and an F1-score of 0.77, followed closely by LaBSE and XLM-Roberta. Confusion matrix analysis revealed that categories such as Normal, Anxiety, and Personality Disorder were classified with high accuracy, whereas Depression and Suicidal posed greater challenges due to overlapping linguistic patterns. Error analysis using manual inspection, PCA visualization, and SHAP explainability provided further insights. PCA highlighted semantic overlap between related categories, while SHAP demonstrated that emotionally charged terms like “ ” (fear) and “ ” (suicide) strongly influenced model predictions, whereas ambiguous terms such as “ ” (sadness) contributed to misclassifications. These analyses enhance the interpretability and reliability of the model outcomes. Overall, the results indicate that Indic-specific transformer models are highly effective for sentiment analysis in low-resource languages like Telugu. Moreover, integrating explainability techniques such as PCA and SHAP can provide deeper understanding of model behavior. Together, these findings highlight the potential of transformer-based sentiment analysis as a valuable tool for early detection and monitoring of mental health signals in Telugu social media.

## VII. Limitations and Future scope

Despite encouraging results, several limitations should be noted. The dataset, although balanced, was sourced exclusively from social media platforms, which may not fully capture clinical expressions of mental health. Handling code-mixed Telugu-English text remains challenging, particularly when slang, idioms, or figurative language are involved. Misclassifications were most common in closely related categories, such as Depression and Suicidal, where subtle contextual differences are difficult for the model to capture. Furthermore, while SHAP offered token-level interpretability, the overall black-box nature of transformer models limits transparency in sensitive applications like mental health monitoring. Future work can focus on several promising directions. Domain-adaptive pre-training on Telugu mental health specific corpora could improve contextual understanding and reduce errors in nuanced categories. Expanding the dataset to incorporate cultural idioms, figurative expressions, and spoken discourse may further improve generalization. Integrating context-aware modelling at the discourse or conversational level could also reduce confusion between overlapping classes such as Depression and Suicidal. Another important direction is the development of explainable and trustworthy AI systems. Combining SHAP with attention visualization or counterfactual reasoning can provide richer insights into model predictions, increasing acceptance among clinicians and end-users. Finally, the deployment of these models in real-time mobile or web applications could enable scalable, accessible, and culturally sensitive digital mental health support for Telugu-speaking communities worldwide.

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