Mental Health Analysis and Feedback System Using NLP and ML

Mr. Vinayak S [1], Gagan R K [2], Adarsh G B [3], Anushree C [4], Chandana D [5]

[1] *Mr. Vinayak S Asst. Prof, Dept. of AD, East West Institute of Technology, Bengaluru*
[2] *Gagan R K, Dept. of AD, East West Institute of Technology, Bengaluru*
[3] *Adarsh G B, Dept. of AD, East West Institute of Technology, Bengaluru*
[4] *Anushree C, Dept. of AD, East West Institute of Technology, Bengaluru*
[5] *Chandana D, Dept. of AD, East West Institute of Technology, Bengaluru*

---***---

Abstract - Mental health concerns have become one of the most pressing global issues of the 21st century, affecting individuals across age groups, geographies, and professions. With the rising prevalence of anxiety, stress, and depression, early detection and timely feedback systems are essential to prevent escalation. This research presents the Mental Health Analysis and Feedback System Using Natural Language Processing (NLP) and Machine Learning (ML)—a web-based solution capable of analyzing user-generated text to identify emotional states and potential signs of psychological distress. By integrating NLP-based text preprocessing, emotion classification using ML models, and an intelligent feedback mechanism, the proposed framework facilitates an accessible and scalable method for mental health assessment. The system leverages publicly available datasets, including GoEmotions and Emotions Dataset for NLP, to train robust classification models capable of multi-label emotion detection. The output from these models is used to generate empathetic, non-clinical feedback for users. This study contributes toward the intersection of artificial intelligence and digital health, demonstrating how computational linguistics and supervised learning techniques can be harnessed for social good.

Key Words: Mental Health, NLP, Machine Learning, Emotion Detection, Web Application, Psychological Analysis

1. INTRODUCTION

Mental health is a crucial component of overall human well being, encompassing emotional, psychological, and social aspects of life. According to the World Health Organization (WHO) [10], one in four individuals will experience some form of mental health challenge in their lifetime. The growing prevalence of stress, anxiety, and depression has prompted researchers to explore digital interventions that enable early detection and non-invasive monitoring of psychological conditions.

The increasing availability of online communication and user-generated text data presents an opportunity to detect emotional cues embedded in language. Techniques from Natural Language Processing (NLP) have shown promising potential in extracting sentiment, emotion, and psychological features from text. When integrated with Machine Learning (ML) models NLP can be applied to identify patterns of emotional distress and offer meaningful insights into users' mental states.

This paper introduces a web-based application that analyzes user input text and provides feedback aligned with the detected emotional tone. The Mental Health Analysis and Feedback System operates by processing text using NLP methods, classifying emotions using supervised ML algorithms, and generating personalized, empathetic feedback. The system architecture integrates a user interface built with HTML, CSS, and Flask backend services, connecting to trained ML models that handle text processing and prediction. This research aims to bridge the gap between AI-driven emotional analytics and real-world mental health applications by presenting a system that is both technically robust and ethically responsible.

2. LITERATURE SURVEY

The use of artificial intelligence in healthcare has gained significant attention over the last decade, particularly in mental health prediction. Kroenke et al. [1] proposed the PHQ-9, a validated instrument to measure depression severity, which remains a key foundation for computational emotion analysis. Google Research [2] introduced GoEmotions, a large-scale dataset containing over 58,000 human-labeled Reddit comments across 27 emotion categories, which has since become a benchmark for emotion classification research.

Mahadevan and Kapoor [3] discussed ethical frameworks and responsible AI deployment in healthcare, emphasizing transparency and fairness in predictive systems. Nguyen et al. [6] utilized ML classifiers, such as Support Vector Machines (SVM) and Naïve Bayes, for depression detection using social media text. Zhao et al. [5] incorporated contextual embeddings from BERT to enhance emotion recognition accuracy, marking a significant advancement over traditional TF-IDF-based approaches.

Further, Lin and Xu [7] highlighted the role of sentiment and emotion analysis in digital mental health monitoring, while Choudhary and Singh [8] developed ML models to predict psychological distress from structured survey data. Sahu and Sharma [9] implemented an interactive mental health chatbot integrating NLP and ML for user engagement and guidance. From the reviewed works, it is evident that combining linguistic features with supervised learning yields reliable emotion classification. However, limited research focuses on integrating these techniques into user-accessible web platforms providing actionable feedback—a gap addressed by this study.

3. METHODOLOGY

The proposed system follows a multi-layered design combining NLP, ML, and web development components. The overall workflow consists of data preprocessing, feature extraction, model training, and feedback generation.

A. Data Preprocessing: Textual data collected from emotion datasets undergoes a sequence of preprocessing operations. The system uses tokenization, stopword removal, and lemmatization to clean input text. The NLTK and SpaCy libraries are used for linguistic preprocessing. Lowercasing and punctuation normalization are applied to standardize inputs.

B. Feature Extraction: After cleaning, text data is vectorized using Term Frequency–Inverse Document Frequency (TF IDF) and contextual word embeddings derived from BERT. The TF-IDF approach quantifies word importance in a sentence, while BERT embeddings capture semantic and syntactic nuances crucial for emotion recognition.

C. Model Training: The preprocessed and vectorized data are fed into multiple ML algorithms such as Support Vector Machine (SVM), Logistic Regression, and Random Forest. Grid search and cross-validation are employed for hyperparameter optimization. The trained models are evaluated using metrics such as accuracy, precision, recall, and F1-score.

D. Feedback Generation: The predicted emotion label (e.g., joy, sadness, anger, fear) triggers a corresponding feedback message aimed at emotional well-being. For instance, if a user's input indicates sadness, the system generates encouraging messages and relevant coping suggestions. This component is rule-based and designed to align with WHO recommended non-clinical support principles.

E. Ethical Considerations: The system is explicitly non diagnostic; it provides general guidance rather than medical advice. Data privacy, informed consent, and ethical AI practices are prioritized throughout implementation, following guidelines from Mahadevan and Kapoor [3]..

4. SYSTEM IMPLEMENTATION

The system is deployed as a web-based platform built using Python Flask. The backend integrates the ML model and NLP pipeline, while the frontend provides a responsive interface for user interaction. When a user submits text through the interface, the Flask server routes the input to the prediction module. The processed text is passed to the trained ML classifier, which outputs emotion probabilities. Based on these predictions, a dynamic feedback message is generated and displayed in real-time.

The architecture (shown in Fig. 1) illustrates the interaction between the key modules: User Interface (UI), Backend (Flask), Machine Learning Model, and Database/Storage. Flask was chosen for its lightweight nature, allowing seamless integration with scikit-learn models. HTML, CSS, and JavaScript ensure a minimal yet functional user experience. The overall design adheres to ethical AI principles by avoiding data retention and ensuring anonymity.

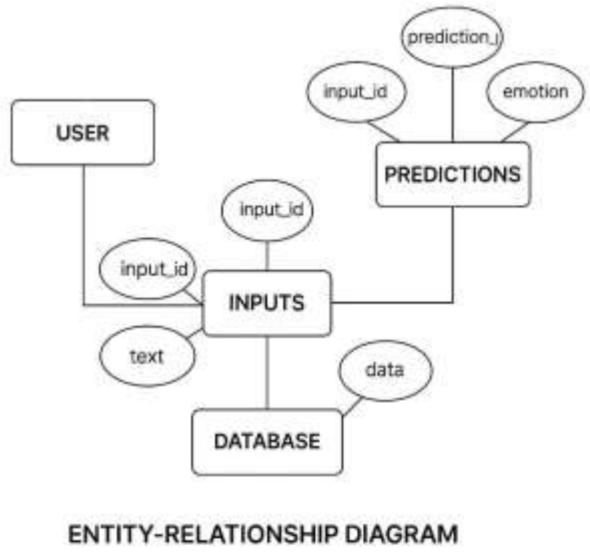

Fig. 1 System Architecture of the Proposed Model

5. TECHNICAL IMPLEMENTATION

The application was implemented using Python 3.11 and Flask as the lightweight web framework. Scikit-learn handled machine learning pipelines, while NLTK and SpaCy facilitated NLP preprocessing.

The GoEmotions dataset provided labeled samples for model training, while BERT-based embeddings improved contextual accuracy. Model performance was benchmarked using multiple algorithms, with the SVM achieving balanced accuracy across emotion categories.

The deployment workflow:

1. User submits text → Backend receives input.

2. NLP pipeline processes and vectorizes the text.

3. Model predicts emotion label (e.g., sadness, joy).

4. Flask server renders the emotion result and feedback.

The backend does not store user messages or logs, ensuring zero data persistence. This privacy-centric design makes the system suitable for educational, research, and public mental health use.

6. SECURITY AND ETHICAL CONSIDERATION

Security and ethics form the backbone of this project. As mental health data is highly sensitive, the system enforces strict privacy principles:

- Data Anonymity: No personal identifiers are stored or logged.
- No Clinical Diagnosis: The feedback is informative, not therapeutic.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

- Transparency: The user is informed that predictions are AI-based.

Bias Mitigation: The model is tested for class imbalance and retrained periodically.

Following the framework outlined by Mahadevan and Kapoor [3], the design promotes Responsible AI — focusing on fairness, accountability, and inclusivity. The system ensures compliance with ethical AI practices, emphasizing accessibility without replacing human counseling.

7. LIMITATIONS AND FUTURE WORK

While promising, the proposed model has certain limitations.

- Dataset Bias: Most training data are sourced from Western social media, limiting cross-cultural emotional understanding.
- Language Restriction: The system currently supports only English inputs.
- Emotion Ambiguity: Subtle emotions like "grief" or "nostalgia" may overlap semantically.

Future enhancements include:

- Incorporating multilingual embeddings (e.g., mBERT) for wider.
- linguistic coverage. Integrating multimodal inputs (voice tone, facial emotion).
- Adopting transformer-based fine-tuning for improved contextual learning.
- Developing adaptive chatbot extensions to provide conversational engagement with ethical safeguards.

8. CONCLUSION

This paper presented a Mental Health Analysis and Feedback System that leverages NLP and ML techniques to assess emotional states and provide constructive feedback. Through extensive use of linguistic preprocessing and classification models, the system demonstrates the capability to interpret textual data for emotion recognition. By integrating these components into a web-based interface, the project bridges the gap between machine learning research and accessible digital health tools.

The results affirm that language-based cues can serve as reliable indicators of emotional states, forming the foundation for early intervention strategies. Future enhancements may involve integrating deep learning architectures, multilingual datasets, and context-aware chatbots capable of empathetic dialogue. Expanding collaboration with clinical professionals could further refine feedback mechanisms to align with therapeutic frameworks while maintaining ethical and privacy safeguards.

REFERENCES

[1] Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2020). The PHQ-9: A Brief Depression Severity Measure. Journal of General Internal Medicine, 16(9), 606–613.

[2] Google Research. (2021). GoEmotions: A Dataset for Fine-Grained Emotion Classification. arXiv preprint arXiv:2005.00547.

[3] Mahadevan, B., & Kapoor, K. (2024). Ethical Applications of Artificial Intelligence in Healthcare. IEEE Access, 12, 23345–23357.

[4] Praveen Govi. (2023). Emotions Dataset for NLP (emotion.csv). Kaggle. Retrieved from https://www.kaggle.com/praveengovi/emotions-dataset-for nlp

[5] Zhao, L., et al. (2023). Emotion Recognition using BERT Embeddings. IEEE Transactions on Affective Computing, 14(2), 678–690.

[6] Nguyen, T., Do, T., & Pham, Q. (2022). Depression Detection from Textual Data using Machine Learning Techniques. Procedia Computer Science, 200, 497–504.

[7] Lin, C., & Xu, H. (2023). Sentiment and Emotion Analysis in Mental Health Applications using NLP. International Journal of Artificial Intelligence Research, 47(3), 152–163.

[8] Choudhary, R., & Singh, A. (2024). Machine Learning Models for Predicting Psychological Distress. Journal of Information Technology & Software Engineering, 14(1), 88–96.

[9] Sahu, S., & Sharma, P. (2023). An Interactive Mental Health Chatbot using NLP and ML Techniques. IJITEE, 13(5), 50–57.

[10] World Health Organization (WHO). (2023). Mental Health: Strengthening Our Response. Geneva: WHO Publications. Retrieved from https://www.who.int/news room/fact-sheets/detail/mental-health-strengthening-our response