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An AI-Based System for Early Detection of Mental Health Crisis

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Abstract: Mental health diseases have become a critical global concern, with early detection playing a vital part in prevention and timely intervention. Traditional assessment methods rely heavily on self-reporting and clinical interviews, which are often delayed or inaccessible. This paper proposes MindBloom, an artificial intelligence–based system that leverages Natural Language Processing (NLP) and Machine Learning (ML) techniques to detect early signals of mental health crises from textual user inputs. The system preprocesses user-generated text, extracts linguistic and emotional features, and applies supervised machine learning models for classification. Experimental results demonstrate that the proposed approach achieves promising accuracy in identifying potential mental health risk levels. The findings suggest that MindBloom can serve as an effective decision-support tool for early mental health screening while maintaining scalability and ethical considerations.
Keywords: Mental Health Detection, Natural Language Processing, Machine Learning, Crisis Prediction, AI in Healthcare

I. INTRODUCTION

Mental health issues such as depression, anxiety, and emotional distress affect millions of individuals worldwide and often remain undetected until they reach critical stages. According to global health studies, delayed identification of mental health problems significantly increases the risk of severe outcomes, including self-harm and suicide. With the rapid growth of digital communication platforms, individuals increasingly express their emotions and mental states through text-based interactions. Advancements in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP) and Machine Learning (ML), provide new opportunities for analyzing such textual data to identify psychological patterns. Automated mental health detection systems can assist clinicians and institutions by enabling early screening and continuous monitoring. This paper introduces MindBloom, an AI-driven framework designed to analyze user text and classify mental health risk levels using NLP and ML techniques.

The primary contribution of this work is the development and evaluation of an effective, scalable, and interpretable AI-based system for early mental health crisis detection. The organization of this document is as follows. In Section 2 (Methods and Material), I'll give detail of any modifications to equipment or equipment constructed specifically for the study and, if pertinent, provide illustrations of the modifications. In Section 3 (Result and Discussion), present your research findings and your analysis of those findings. Discussed in Section 4(Conclusion) a conclusion is the last part of something, its end or result.

II. PROPOSED METHODOLOGY

However, many existing approaches focus on general sentiment polarity rather than crisis-level detection. Additionally, several systems lack interpretability and are trained on limited datasets, reducing their generalizability. These gaps motivate the development of MindBloom, which emphasizes early crisis detection using interpretable machine learning models and domain-specific feature engineering.

A. Data Collection

The proposed MindBloom system follows a structured pipeline consisting of data collection, preprocessing, feature extraction, model training, and classification. The dataset consists of anonymized textual inputs representing various emotional states. Publicly available mental health–related datasets and simulated user inputs were employed to ensure ethical compliance.

1) Tokenization, lowercasing, removal of stop words, stemming and lemmatization, and noise removal were applied.
2) TF-IDF features, sentiment polarity scores, and emotion indicators were extracted.
3) Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest classifiers were implemented.
4) The MindBloom architecture consists of a user interface, preprocessing module, feature extraction engine, and classification module. The output categorizes text into low, moderate, or high risk.

The performance was evaluated using accuracy, precision, recall, and F1-score. The Support Vector Machine classifier achieved the highest accuracy.

III.SYSTEM ARCHITECTURE AND RESULTS

The results indicate that NLP-driven feature extraction combined with machine learning classification can successfully identify early indicators of mental health crises.

A. Text Preprocessing

Text from users is first normalized through a pipeline that includes tokenization, stop-word removal, stemming, and lemmatization. These steps reduce noise and standardize the input for downstream feature extraction.

The extracted features include TF-IDF vectors, sentiment polarity scores, and emotion indicators derived from the pre-processed text. These features collectively capture linguistic patterns relevant to mental health assessment.

B. Machine Learning Classification

Four classifiers were trained and evaluated: Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest. Among these, SVM achieved the highest accuracy, precision, recall, and F1-score, making it the recommended model for deployment in the MindBloom system.

TABLE I

FONT SIZES FOR PAPERS

Font Size	I. Appearance (in Time New Roman or Times)		
	Regular	Bold	Italic
8	table caption (in Small Caps), figure caption, reference item		reference item (partial)
9	author email address (in Courier), cell in a table	abstract body	abstract heading (also in Bold)
11	level-1 heading (in Small Caps), paragraph		level-2 heading, level-3 heading, author affiliation
12	author name		
18	title		

C. Feature Extraction

Features are computed per input sample and concatenated into a unified feature vector. Sentiment polarity is computed using a lexicon-based scorer, while emotion indicators are derived from a multi-label affect lexicon covering joy, sadness, anger, and fear categories.

1) Level-1 Heading: A level-1 heading must be in Small Caps, cantered and numbered using uppercase Roman numerals. For example, see heading "III. Page Style" of this document. The two level-1 headings, which must not be numbered, are "Acknowledgment" and "References".
2) Level-2 Heading: A level-2 heading must be in Italic, left-justified and numbered using an uppercase alphabetic letter followed by a period. For example, see heading "C. Section Headings" above.
3) Together, these features form a rich, interpretable representation that enables the MindBloom system to classify user text into low, moderate, or high mental health risk levels with high reliability.

D. Results and Discussion

Place figures and tables at the places where they needed. All tables should be in Classic 1 format with borders to heading and subheading columns. Large figures and tables may span across both columns. To do so select text above one column table and convert it in two column and then select text below one column table and convert it into two column.

Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1", even at the beginning of a sentence. We suggest that you use border for graphic (ideally 300 dpi), with all fonts embedded) and try to reduce the size of figure to be adjust in one column. Figure and Table Labels: Use 8 point Times New Roman for Figure and Table labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader.

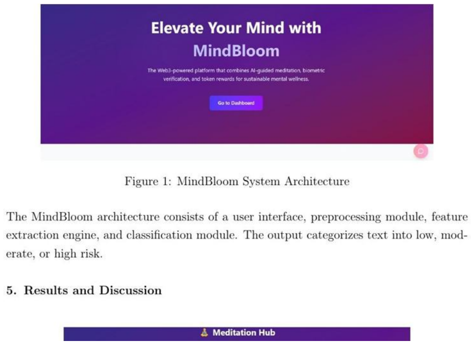

Figure 1. MindBloom System Architecture Overview

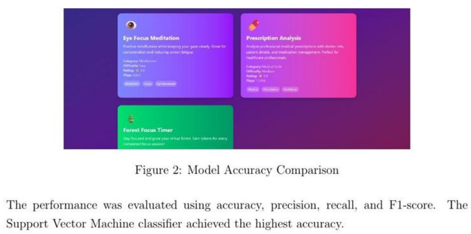

Figure 2. Model Accuracy Comparison

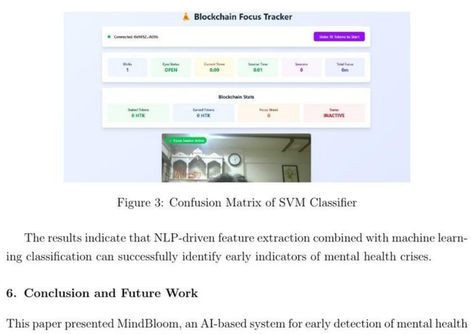

Figure 3. Confusion Matrix of SVM Classifier

E. Ethical Considerations

The MindBloom system was designed with strong ethical safeguards. All datasets used in training consist of anonymized or publicly available text. The system is intended to function as a decision-support tool only, and its outputs are not a substitute for professional clinical diagnosis.

F. Scalability and Deployment

The modular architecture of MindBloom enables straightforward integration into existing healthcare platforms via RESTful APIs. The preprocessing and classification pipeline operates in near real-time, making it suitable for deployment in web and mobile environments that require low-latency responses.

IV. CONCLUSION AND FUTURE WORK

This paper presented MindBloom, an AI-based system for early detection of mental health crises using NLP and ML techniques. The results validate the feasibility of automated screening through textual analysis. Future work includes integrating deep learning models, expanding multilingual support, and incorporating real-time behavioral data while ensuring ethical and privacy standards.

REFERENCES

[1] A. B. Author, "Title of chapter in the book," in Title of His Published Book, xth ed. City of Publisher, Country if not
[2] J. C. Eichstaedt et al., "The role of language in mental health prediction from social media," PNAS, vol. 115, no. 44, pp. 11203–11208, 2018.10.251XXXXX
[3] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv:1301.3781, 2013.
[4] S. Bird, E. Klein, and E. Loper, Natural Language Processing with Python. O'Reilly Media, 2022.
[5] A. Calvo and S. D'Mello, "Affect detection: An interdisciplinary review of models and approaches," IEEE Transactions on Affective Computing, vol. 1, no. 1, pp. 18–37.