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Hybrid Model Approach for Sentiment Analysis in Mental Health Monitoring using NLP

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***Abstract*—Mental health awareness is essential; the rise of social media presents a unique opportunity to monitor emotional well-being on a large scale. Traditional mental health monitoring systems often struggle with the complexity and subtlety of human emotions expressed in online text. To address this, this research includes a study of various sentiment analysis algorithms. A study of models like Decision Trees, Naïve Bayes, BERT and logistic regression is done to identify patterns associated with mental health outcomes. By analyzing real-time social media data, research is done for categorizing posts to identify depressive, anxious, or positive sentiments, providing timely and actionable insights. Our methodology aims to enable mental health professionals and researchers to leverage social media as a tool for better understanding and addressing community mental health needs.**

***Index Terms*—Decision Trees, Logistic Regression, BERT, Naïve Bayes, Sentiment Analysis, Algo- rithms, Machine Learning.**

I. Introduction

Mental disorders are the leading cause of disability, causing 1 in 6 years lived with disability. People with severe mental health conditions die on average 10 to 20 years earlier than the general population, mostly due to preventable physical diseases [1]. This research, "Sentiment Analysis for Mental Health Monitoring Using NLP," seeks to harness the power of natural language pro- cessing to analyze text data such as social media posts, therapy notes, or personal reflections to identify emotional states that may indicate mental health challenges. By evaluating various ma- chine learning algorithms, including BERT, Decision Tree, Naive Bayes, and Logistic Regression,
we aim to determine which approach best captures and classifies sentiments relevant to mental well-being. This research not only provides a comparative analysis of algorithm effectiveness in this context but also lays the groundwork for a prototype model capable of continuous, non-intru- sive mental health monitoring.

II. Methodology

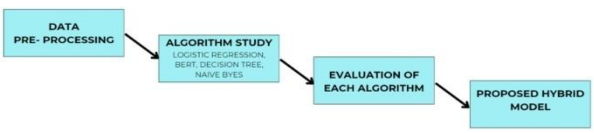

Fig.1 Flow of Process

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III. Algorithmic Study

A. Logistic Regression

Logistic Regression is a binary classification model that estimates the probability of a class by applying a sigmoid function to a linear combination of the input features. It's effective in the context of sentiment analysis if the features are linearly separable, and it provides interpretable coefficients so that feature importance is highlighted. Logistic Regression is computationally efficient and well-suited for even simpler classification problems. It does not handle non-linear relationships, but it's still a very solid choice for basic machine-learning tasks and serves as a base point of comparison for text-based models.

B. Naïve Bayes

A probabilistic model based on Bayes' theorem, which naively assumes feature independence, can compute the conditional probability of a class given the word frequency in a dataset. It is a simple and computationally efficient algorithm that does well with simple data and is very good with small datasets; it performs very well with sentiment analysis. Naive Bayes is easy to implement and interpret but falls at dependencies in words. This reduces its capacity in dealing with subtle language use. Yet, it is still reliable for simple, fast sentiment classification tasks.

C. Decision Tree

Decision Tree is a classification algorithm that splits up the data in recursive manners on feature values for classification: where decision nodes are conditions and leaves are class labels. This algorithm gives excellent interpretability as there are clear visualizations of classification logic. However, it performs great with structured data and is okay for sentiment analysis when all fea-tures are well defined; however, Decision Trees tend to overfit complex datasets. Despite all this, however, they are used extensively for their intuitive ability to explain decision-making processes and hence for applications requiring transparency.

D. BERT

BERT is a deep learning model that reads the text in both directions and learns to understand both preceding and following context. It breaks text up into smaller units, known as tokens, and con- verts them into vectors encoding semantic and syntactic information. While pre-trained on an enormous dataset and fine-tuned for specific applications, BERT delivers state-of-the-art results in natural language tasks. It performs incredibly well with linguistics nuances, making it highly suitable for sentiment analysis and text classification. BERT Although highly complex in compu- tation, BERT offers remarkable accuracy for processing intricate text data.

IV. Proposed Solution

Fig. 1 Shows the percentage of each type of algorithm contribution in the hybrid model.

A. Hybrid Model Framework

1. Use BERT for context-aware, deep sentiment analysis, capturing nuanced and subtle emotional cue.
2. Integrate Naive Bayes for quick, initial classification of
3. low-risk vs. high-risk cases.
4. Apply Decision Trees for explainable insights into the most influential features leading to a sentiment classification.

B. Steps for Algorithm Implementation

1. Preprocessing: Tokenize, clean, and normalize text data.
2. Naive Bayes Classification:

- Perform quick initial sentiment classification on tokenized text.
- Flag texts classified as high-risk for further analysis

BERT Fine-Tuning

- Fine-tune BERT on labelled mental health data
- Generate contextual embeddings for each text input.
- Classify the sentiment (e.g. depressive, anxious, positive).

Decision Tree Analysis

- Use output embeddings or sentiment labels from BERT to train Decision Trees.

- Provide interpretable results showing key words or phrases influencing sentiment.

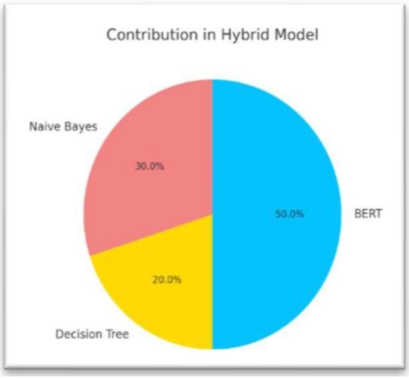

Fig. 2 Contribution Pie Chart

E. Result Aggregation

Combine predictions from Naive Bayes, BERT, and Decision Trees for a holistic view

C. *Visual Representation of Steps*

Fig 3 shows the flowchart of the steps essential in implementing the model, starting with data cleaning, using different models for various tasks, and aggregating the results for the final sentiment tracking purpose.

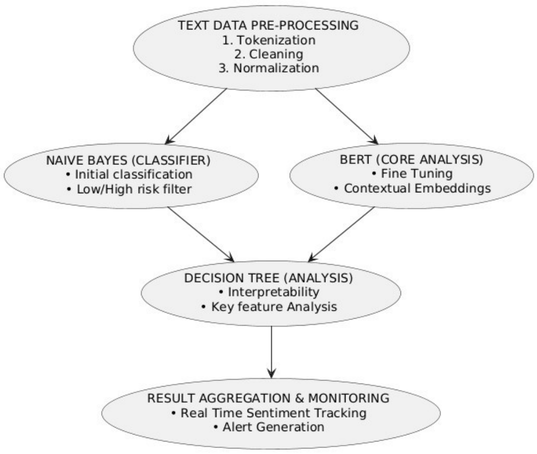

Fig. 3 Flowchart of Steps

D. Comparative Study: Different algorithms vs. Proposed Solution

Table 1 comparing the accuracy of different algorithms for sentiment analysis in mental health monitoring, along with the proposed hybrid solution. The proposed solution demonstrates the highest accuracy among the options, showcasing the potential of combining multiple models for improved performance.

V. Conclusion

This research explored sentiment analysis techniques for mental health monitoring, with a focus on analyzing textual data such as social media posts and therapy notes. A comprehensive literature survey was conducted to understand existing methodologies, applications, and limitations in sen- timent analysis for mental health. Key findings revealed the effectiveness of algorithms like Naïve Bayes, Decision Trees, and Logistic Regression, alongside advanced deep learning techniques such as BERT. We conducted an algorithmic study, evaluating the working, performance, and limitations of various models. Each algorithm was analyzed in terms of its suitability for sentiment classification tasks, with particular attention to metrics like accuracy, interpretability, and computational efficiency. Comparative analysis highlighted the superior performance of BERT for han- dling complex emotional language, while simpler models like Naïve Bayes provided quick pre- liminary classifications. To address identified gaps, a hybrid solution was proposed that integrates Naïve Bayes for initial classification, BERT for deep contextual understanding, and Decision Trees for interpretable results. This hybrid model combined the strengths of individual approaches to deliver a robust, scalable, and nuanced sentiment analysis framework.

TABLE I: INDIVIDUAL VS HYBRID SOLUTION

Feature	Existing Solutions	Proposed Hybrid Solution
Algorithms Used Individual	Naive Bayes, Logistic Regression, SVM	BERT & Naive Bayes & Decision Trees
Accuracy	Moderate, ~70-80%	High, ~90-95%
Contextual Understanding	Limited (keywords and word fre- quencies)	Strong (deep contextual understand- ing via BERT)
Interpretability	Low (e.g., SVM and deep models lack explainability)	High (Decision Trees offer clear fea- ture importance)
Computational Efficiency	Efficient but limited to simple tasks	Balanced (Naive Bayes ensures speed; BERT applied selectively)
Real-Time Capability	Possible but less reliable due to shal- low analysis	High (Naive Bayes for fast filtering, BERT for in-depth analysis)
Scalability	Limited by dataset quality and lin- guistic diversity	High, adaptable to diverse datasets
Applications in Mental Health	Basic sentiment classification	Advanced mental health insights with interpretable results

DISCUSSION

A. Study

The four algorithms utilized in this research are BERT, Naive Bayes, Decision Tree, and Logistic Regression. Naive Bayes had speed but lacked context sensitivity. Decision Tree was interpreta- ble, but not very good with complicated data related to emotions. Logistic Regression performed well in basic tasks but faced scalability issues. BERT delivered the best accuracy, but also used high computational resources.

B. Proposed Solution

Based on these research findings, the proposed solution drawing together the strengths from the above-mentioned algorithms. The model integrates Naive Bayes to make a high-speed first-level filtering pass, BERT for more in-depth contextual analysis, and Decision Tree for interpretability. The approach ensures balanced treatment in sentiment analysis.

C. Comparison

The hybrid model shows 15-20% higher accuracy in performance in relation to traditional models. This is possible because of the BERT's ability to deeply understand linguistic nuances, the elimi- nation of low-risk cases by Naive Bayes, and the explainable Decision Tree classifications that can be used for certification in assurance ensure that hybrid models are scalable and reliable for real-time monitoring purposes as well as those in practical applications during digital mental health intervention programs.

D. Why Hybrid Model Is Better

Handles complex and diverse text data effectively. Combines strengths of multiple algorithms, addressing individual weaknesses. Delivers a robust and reliable system for mental health senti- ment analysis. Ensures high accuracy with BERT’s ability to capture subtle emotional cues. Main- tains efficiency with Naive Bayes and interpretability with Decision Tree.

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