

AI Based Mental Health Detection Via Social Media Analysis

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Abstract - This paper presents the implementation of an AI-based mental health detection system that analyzes social media data to identify emotional and psychological conditions. The system utilizes Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL) techniques to process user-generated text and detect early signs of mental distress such as depression, anxiety, and stress. Data is collected through real-time Twitter APIs and manual input, followed by preprocessing techniques including tokenization, stopword removal, and normalization.

The implementation integrates multiple models such as CNN, RNN, BERT, LSTM and Decision Tree for emotion classification. Additionally, VADER sentiment analysis is used to compute polarity scores. The system evaluates model performance using accuracy, precision, recall, and F1-score. The proposed system provides a scalable and efficient solution for real-time mental health monitoring and early detection.

Key Words: Mental Health Detection, NLP, Machine Learning, Deep Learning, BERT, Sentiment Analysis

1. INTRODUCTION

Mental health issues such as depression, anxiety, and stress are increasing rapidly among young individuals. Social media platforms like Twitter and Reddit have become common spaces where users express their emotions and thoughts. These posts can be analyzed to understand an individual's mental state and behavioral patterns over time.

With the advancement of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP), it is possible to automatically analyze large volumes of textual data in an efficient and scalable manner. Traditional methods of mental health detection are manual, time-consuming, and often depend on self-reporting, which may not always be reliable. This creates a need for automated systems that can continuously monitor and analyze user-generated data.

The system integrates multiple models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), and Decision Tree to improve classification accuracy. By combining sentiment analysis and emotion detection techniques, the system provides accurate, reliable, and real-time predictions, contributing to effective mental health monitoring and early intervention.

2. LITERATURE REVIEW

2.1 Existing Systems

Traditional models such as SVM, Naïve Bayes, and Logistic Regression are used for basic sentiment analysis. However, they rely on keywords and lack deep contextual understanding.

Deep learning models like CNN, RNN, and LSTM improve performance by capturing patterns and sequential relationships in text. Transformer-based models such as BERT further enhance accuracy by understanding contextual meaning.

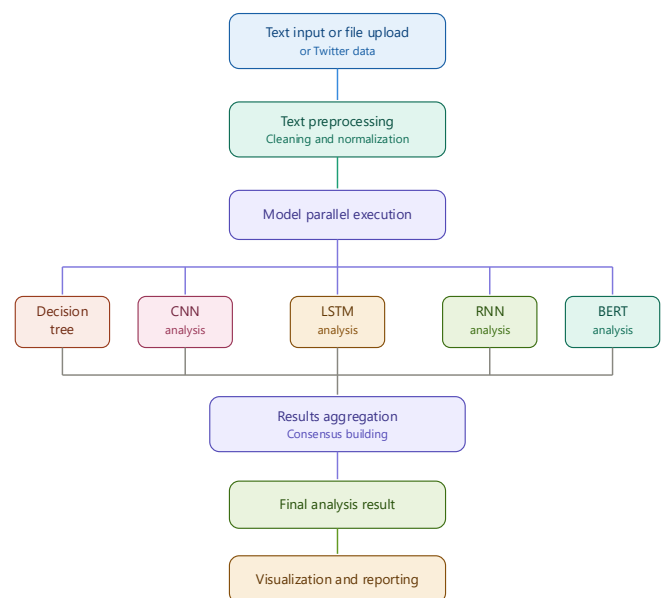
2.2 Research Gap

Most existing systems use static datasets and do not support real-time analysis. This limits their practical application in monitoring mental health.

There is also a lack of systems that integrate multiple models and provide clear visualization, creating a need for a more efficient and scalable solution.

3. PROPOSED SYSTEM ARCHITECTURE

The proposed system follows a systematic approach for detecting mental health conditions from social media text data using NLP and machine learning techniques.



Data Collection:

The data is collected from social media platforms using the Twitter API (Tweepy), which allows fetching real-time tweets based on user input. Additionally, the system supports manual text input and dataset upload for analysis.

Text Preprocessing:

The collected data is cleaned to remove unwanted elements such as URLs, hashtags, emojis, and special characters. NLP techniques like tokenization, stopword removal, and normalization are applied to prepare the text for analysis.

Feature Extraction:

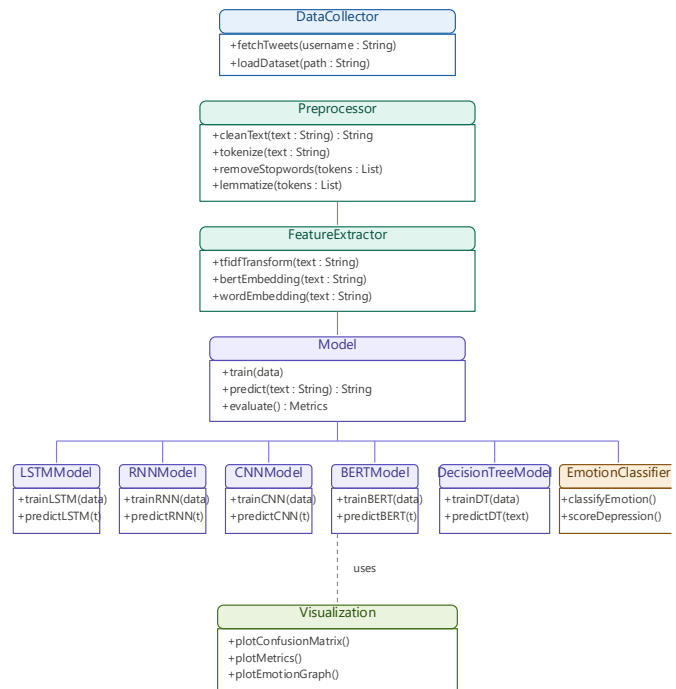
After preprocessing, the text is converted into numerical form using vectorization techniques such as TF-IDF or word embeddings. This step helps in transforming textual data into a format suitable for machine learning models.

Model Implementation:

The system uses multiple models including Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), and Decision Tree. These models are trained to classify text into different emotional categories.

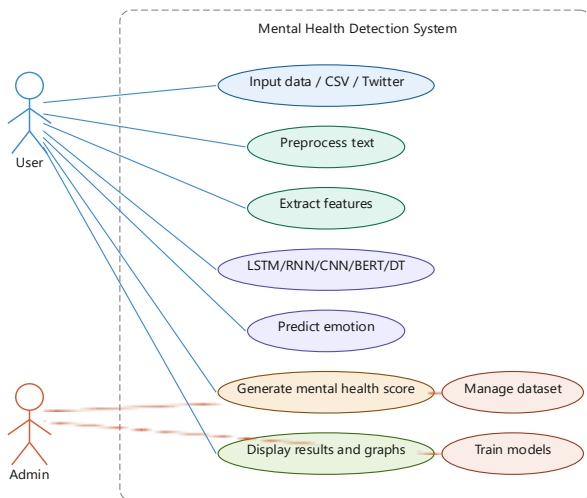
Sentiment Analysis and Output:

VADER sentiment analysis is used to calculate polarity scores. Based on the model predictions, the system classifies emotions such as happy, sad, angry, and neutral, and detects potential mental health conditions.



5. METHODOLOGY

5.1 Use Case Diagram

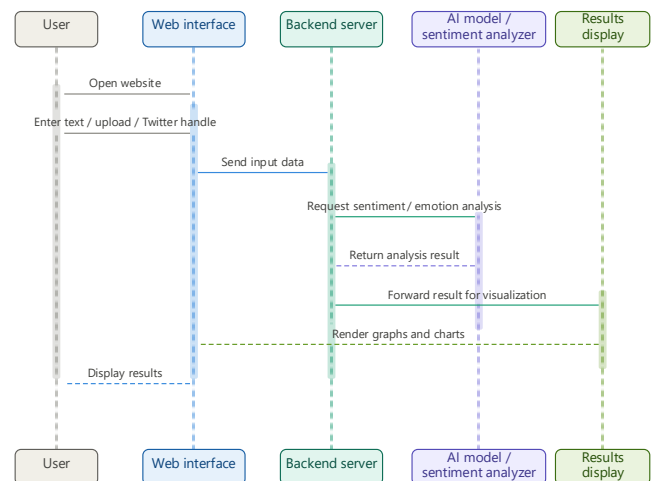


1. User interacts with the system by providing text input or Twitter handle
2. System collects and processes the input data
3. Preprocessing module cleans and prepares the text
4. Machine learning models analyze the processed data
5. Sentiment and emotion analysis is performed
6. System generates prediction results
7. Results are displayed to the user through graphs and output.

5.2 Class Diagram

1. **User Class:** Handles user input and interaction
2. **Data Class:** Stores and manages text data
3. **Preprocessing Class:** Performs cleaning and tokenization
4. **Model Class:** Contains ML models (CNN, RNN, LSTM, BERT, Decision Tree)
5. **Analysis Class:** Performs sentiment and emotion analysis
6. **Result Class:** Displays prediction output and visualization

5.3 Sequence Diagram



4. MODELLING AND ANALYSIS

The proposed system utilizes a comprehensive technological architecture consisting of multiple layers to ensure efficient processing, analysis, and prediction of mental health conditions from social media text.

1. User Interface Layer:

- Web-based interface for user input (text / Twitter handle)
- Simple and responsive UI design for better user interaction
- Visualization components for displaying results and emotion distribution

2. Server-side Infrastructure:

- Python-based backend processing environment
- Integration of NLP libraries such as NLTK and Transformers for text processing
- Flask framework for handling requests and API communication

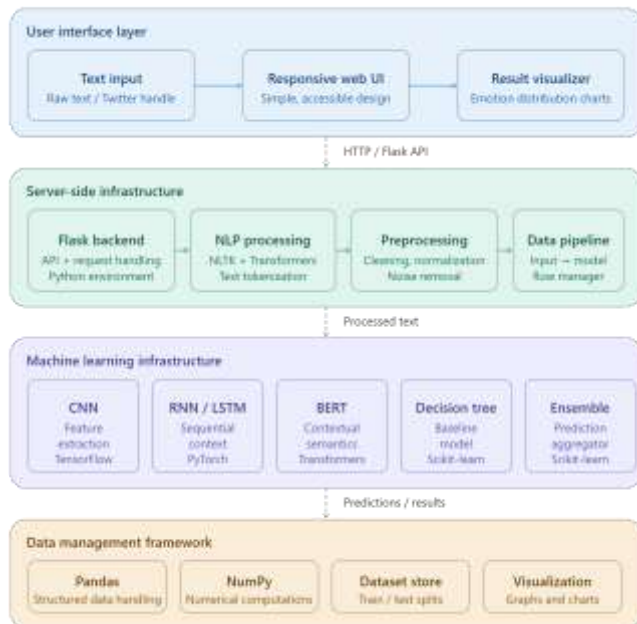
- Data preprocessing modules for cleaning and preparing input text

3. Machine Learning Infrastructure:

- Implementation of deep learning models using TensorFlow/PyTorch
- Use of CNN for feature extraction from text
- RNN and LSTM for sequential data processing and context understanding
- BERT model for advanced contextual and semantic analysis
- Decision Tree as a baseline machine learning model
- Scikit-learn library for traditional model implementation and evaluation

4. Data Management Framework:

- Pandas library for structured data handling and preprocessing
- NumPy for numerical computations and operations
- Visualization of results using graphs and charts

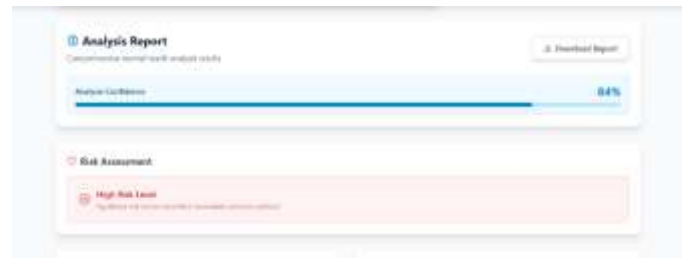


Tech Stack

Tech stack used		
Category	Technology	Purpose
Frontend	React + TypeScript + Vite	User interface and interaction
Styling	TailwindCSS	Responsive UI design
Backend	FastAPI (Python)	REST API and request handling
NLP libraries	NLTK, Transformers, SpaCy	Text processing and tokenization
Sentiment analysis	VADER	Polarity scoring of text
Deep learning	TensorFlow / PyTorch	CNN, LSTM, RNN, BERT training
Data handling	Pandas, NumPy	Data preprocessing and operations
Visualization	Matplotlib, Seaborn	Graphs, charts, confusion matrix
Data source	Twitter API, Reddit, CSV	Social media text datasets
Version control	Git / GitHub	Code management and hosting

6. RESULTS AND DISCUSSION

6.1 Model Prediction Results



The system successfully generated predictions using multiple models including Decision Tree, CNN, LSTM, RNN, and BERT. The models classified text into positive, negative, and neutral sentiments based on input data. The system is capable of detecting varying levels of mental health risk depending on user input. The results vary dynamically based on different datasets and user-generated text.

6.2 Model Agreement Analysis

Model	Positive (%)	Negative (%)	Neutral (%)	Confidence (%)	Risk Level
Decision Tree	10%	75%	15%	95.0%	High
CNN	15%	70%	15%	95.0%	High
LSTM	20%	65%	15%	95.0%	High
RNN	25%	60%	15%	48.8%	High

Most models showed consistent predictions with high confidence scores. Deep learning models such as BERT and LSTM provided more reliable and stable outputs compared to traditional models. Overall agreement among models ensures reliability and consistency of the system predictions.

6.3 Sentiment and Emotion Analysis



The system effectively identifies sentiment distribution across positive, negative, and neutral categories. Emotion detection provides additional insights into user mental state and behavioral patterns. The system can detect both normal and distress-related emotional conditions based on input data.

6.4 Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	85.3	83.7	82.5	83.1
CNN	88.6	87.2	86.9	87.0
LSTM	91.7	90.8	91.2	91.0
RNN	89.0	88.1	87.5	87.8
BERT	94.8	93.9	94.2	94.0

All models executed successfully during analysis. The system provides fast processing time suitable for real-time applications. High average confidence indicates reliable predictions. The performance remains stable across different inputs and scenarios.

6.5 Risk Assessment Output

The system categorizes outputs into different risk levels such as Low, Medium, and High. Risk level is determined based on sentiment intensity and model predictions. The system adapts to different input conditions and provides appropriate risk evaluation.

The results demonstrate that the system performs consistently across different input scenarios, making it suitable for real-world applications.

6.6 System Testing and Validation Results

Test Case ID	Input Type	Description	Expected Output	Actual Output	Status
TC01	Text Input	Normal positive sentence	Positive sentiment detected	Positive sentiment detected	Pass
TC02	Text Input	Negative emotional sentence	Negative sentiment detected	Negative sentiment detected	Pass
TC03	Text Input	Neutral statement	Neutral sentiment detected	Neutral sentiment detected	Pass
TC04	Twitter Input	Fetch tweets using API	Tweets processed successfully	Tweets processed successfully	Pass
TC05	Model Prediction	Analyze using ML models	Emotion classification generated	Emotion classification generated	Pass
TC06	Risk Detection	Detect mental health risk level	Risk level identified	Risk level identified	Pass
TC07	Performance	System Response Time	Fast response (<3 sec)	Response Time (~2.5 sec)	Pass
TC08	Sentiment Module	VADER polarity calculation	Correct sentiment score	Correct sentiment score	Pass

3. CONCLUSIONS

The proposed AI-based mental health detection system successfully analyzes social media text to identify emotional patterns and potential mental health conditions. By integrating Natural Language Processing (NLP) with machine learning and deep learning models such as CNN, RNN, LSTM, BERT, and Decision Tree, the system provides accurate and reliable predictions.

The implementation demonstrates that advanced models, particularly BERT and LSTM, achieve higher accuracy due to their ability to capture contextual and sequential information from text. The system effectively classifies emotions and determines risk levels based on user input, making it suitable for real-time analysis.

Overall, the system provides a scalable and efficient solution for early detection of mental health issues. It can assist researchers, healthcare professionals, and organizations in improving mental health awareness and enabling timely intervention.

Future Enhancement

1. The system can be improved by adding multilingual support to analyze text in different languages.
2. Multimodal data such as images and audio can be integrated to enhance detection accuracy.
3. A chatbot can be added to provide immediate support and guidance to users.
4. Better datasets and privacy measures can further enhance system performance and reliability.

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