# ABSTRACT

The Depression Detection System is a machine learning-based solution designed to identify signs of depression from text data, such as tweets, and provide personalized advice. This project addresses the growing need for scalable and accessible mental health tools by leveraging the capabilities of the Random Forest Classifier. The system follows a structured workflow, starting with data collection from sources like social media. The data undergoes preprocessing, including cleaning, tokenization, and normalization, to prepare it for analysis. Using TF-IDF (Term Frequency-Inverse Document Frequency), the text is transformed into numerical features, which are then fed into the Random Forest model for training. The model learns to classify inputs as "Depressed" or "Not Depressed" based on patterns in the data.

Evaluation of the system demonstrates high accuracy and robustness, with the Random Forest Classifier excelling in handling high-dimensional text data while reducing overfitting. Real-time prediction capabilities allow users to input new text and receive immediate feedback, enhancing the system's usability. Furthermore, the feedback module provides actionable advice based on predictions, encouraging professional help or reinforcing positive habits. While the model performs effectively, limitations such as false positives and challenges with nuanced text are acknowledged, highlighting areas for future improvement. Overall, this project showcases the potential of machine learning to address critical mental health challenges by offering a non-intrusive, efficient, and interpretable solution for early depression detection and support.

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# LIST OF ABBREVATIONS

|  |  |  |
| --- | --- | --- |
| ABBREVATION |  | EXPANSION |
| TF-IDF | - | Term Frequency-Inverse Document Frequency |
| LSTM | - | Long Short-Term Memory |
| SVM | - | Support Vector Machine |
| RF | - | Random Forest |
| ML | - | Machine Learning |
| AI | - | Artificial Intelligence |
| CSV | - | Comma-Separated Values |
| NLP | - | Natural Language Processing |
| UI | - | User Interface |
| DSS | - | Decision Support System |

# CHAPTER 1

# INTRODUCTION

# INTRODUCTION

Mental health issues, particularly depression, have become increasingly prevalent worldwide, affecting millions of individuals across various age groups. Early detection of depression can significantly improve treatment outcomes and reduce the long-term impacts of untreated mental illness. With the rise of social media and digital communication, large amounts of text data are now available, offering a unique opportunity for identifying mental health conditions based on online behavior. This project, the Depression Detector, aims to utilize artificial intelligence (AI) and machine learning (ML) techniques to detect signs of depression through textual data such as tweets. By analyzing sentiment and context within the text, the system provides early identification of depression and offers advice to users on how to proceed.

**1.2 OBJECTIVES**

# The primary objective of the Depression Detector project is to develop an AI-driven system capable of identifying signs of depression from text-based data, specifically tweets. This involves training a machine learning model to analyze patterns and sentiments in user-generated content to predict whether an individual may be suffering from depression. Additionally, the project aims to provide an interactive user experience through a questionnaire, offering advice based on the user's mental health assessment. The long-term goal is to improve mental health awareness and access to early intervention, using advanced AI techniques to support users in managing their well-being.

# 1.3DATA SOURCE DESCRIPTION The data used for this project is sourced from a depression.csv file, which contains a collection of tweets, along with their associated usernames and locations. The key column, tweets, consists of text data, where each tweet reflects a user’s sentiment and emotional state. Although the dataset also includes username and location columns, these are primarily for contextual purposes and do not directly contribute to the depression prediction model. For the sake of simplicity and due to the nature of social media data, the project uses a combination of text-based feature extraction (via TF-IDF) and machine learning algorithms like Random Forest Classifier to analyze these tweets and predict depression.

# 1.4 PROJECT SUMMARIZATION The Depression Detection System is a comprehensive project that integrates natural language processing (NLP) and machine learning (ML) techniques to predict depression by analyzing social media text, such as tweets. The primary goal of the project is to use AI to identify patterns in language indicative of depressive tendencies and provide actionable insights to users.The system begins with the collection of user-generated content, particularly tweets, which often serve as reflections of the users' mental state. These tweets are analyzed for linguistic and emotional cues that could indicate depression. The Data Preprocessing Module prepares the text by cleaning, tokenizing, and normalizing it, removing noise such as URLs, special characters, and irrelevant text. This preprocessing ensures that only meaningful information is used for further analysis.To represent the text in a form that the machine learning model can understand, the system uses TF-IDF (Term Frequency-Inverse Document Frequency) for feature extraction. TF-IDF evaluates the importance of each word in the text, giving higher weights to words that are unique and significant to a particular tweet but appear infrequently across the entire dataset. This step ensures that the model focuses on terms that are more indicative of depression, rather than common or irrelevant words.The preprocessed and transformed data is then fed into a Random Forest Classifier, which serves as the core predictive model of the system. Random Forest is an ensemble learning method that constructs multiple decision trees during training and aggregates their outputs to make accurate and robust predictions. In this project, the classifier learns patterns in the data that are associated with depressive language. For example, the frequent use of words expressing sadness, hopelessness, or fatigue could indicate a depressive state.In addition to analyzing tweets, the system incorporates an interactive questionnaire as an additional feature. The questionnaire is designed to gather insights into the user's mental health through a series of structured questions. These questions evaluate aspects like mood, energy levels, and thought patterns, which complement the text-based analysis. The responses are processed and used to provide immediate feedback on the user's mental health status.The system's prediction output is categorized into two classes: "Depressed" or "Not Depressed." If the user is classified as "Depressed," the system offers actionable advice, such as seeking professional help, engaging in self-care activities, or connecting with mental health support groups. If the user is classified as "Not Depressed," the system provides encouraging feedback to maintain positive mental health habits.Overall, the Depression Detection System combines the power of NLP for analyzing textual data with the reliability of machine learning models to deliver accurate predictions. By integrating an interactive questionnaire and providing personalized advice, the system not only detects depression but also supports users in taking proactive steps toward mental well-being.

# CHAPTER 2

**LITERATURE SURVEY**

**2.1 Deep Learning-Based Comparative Analysis to Track Mental Health Depression Using EEG Data**

**Publication Year :** 2022

**Author : Sarkar, A., Singh, A., Chakraborty, R.**

**Algorithm :** Deep Learning-based methods (likely involving neural networks like CNNs, RNNs, or similar deep learning models for EEG data processing)

**Summary :**

The journal article *"**Deep Learning-Based Comparative Analysis to Track Mental Health Depression Using EEG Data"*. focuses on using deep learning techniques for analyzing EEG (electroencephalogram) data to track mental depression. The study performs a comparative analysis of various deep learning models to assess their effectiveness in detecting depression through EEG signals. It likely discusses the challenges of using EEG data and highlights how deep learning approaches can improve depression detection accuracy.

**2.2. Prediction of Depression Using Bidirectional LSTM with Attention on Social Media Data**

**Publication Year :** 2023

**Author :** Ibitoye A.O., Alina, T**.**

**Algorithm :** Bidirectional Long Short-Term Memory (LSTM) with Attention Mechanism

**Summary :**

The journal article *"**Prediction of Depression Using Bidirectional LSTM with Attention on Social Media Data"* explores the prediction of depression using social media data, employing a Bidirectional LSTM model enhanced with an attention mechanism. LSTM networks are a type of recurrent neural network (RNN) designed to capture temporal patterns in data, while bidirectional LSTMs process data both forward and backward for better context understanding. The attention mechanism helps the model focus on relevant parts of the social media data, improving the prediction accuracy of depression.

**2.3. AI and Machine Learning-Based Decision Support Systems in Mental Health**

**Publication Year :** 2023

**Author :** Higgins, O., et al.

**Algorithm :** General AI and Machine Learning Algorithms

**Summary :**

The article "**.***AI and Machine Learning-Based Decision Support Systems in Mental Health*" discusses the application of AI and machine learning in creating decision support systems for mental health. It covers a range of algorithms that can be used in the diagnosis and management of mental health conditions. The paper likely highlights the benefits, challenges, and future directions of AI-based systems in assisting healthcare professionals in making better decisions related to mental health treatment and diagnosis.

**2.4. Artificial Intelligence for Mental Health and Mental Illnesses: An Overview**

**Publication Year :** 2023

**Author :** Graham, S., et al

**Algorithm :** Various AI Techniques (not specified, but likely includes machine learning, deep learning, and data analytics)

**Summary :**

The article *"**Artificial Intelligence for Mental Health and Mental Illnesses: An Overview* " provides a comprehensive overview of how artificial intelligence is being used in the field of mental health and mental illnesses. The paper covers different AI approaches, such as machine learning, natural language processing, and deep learning, applied to diagnosing and treating mental health conditions. The focus is on the potential of AI to improve mental healthcare delivery, from early diagnosis to personalized treatment plans.

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**2.5. AI Application in the Management of Depressive Disorders: A Bibliometric Analysis**

**Publication Year :** 2023

**Author :** Tran, B.X., et al.

**Algorithm :** AI Methods

**Summary :**

The journal article " *AI Application in the Management of Depressive Disorders: A Bibliometric Analysis"* performs a bibliometric analysis of the use of AI in managing depressive disorders. It reviews existing research and methodologies, categorizing various AI applications in diagnosing and managing depression. The study analyzes trends, key research areas, and the impact of AI technologies in providing treatment solutions for depressive disorders.

**Summary of literature survey**

The literature survey provides insights into the application of machine learning and natural language processing (NLP) techniques for detecting depression, primarily by analyzing social media text. Various studies have explored the use of machine learning models and text mining techniques to predict mental health status based on linguistic features. A study by Sankar et al. (2020) used deep learning-based analysis to track mental health using EEG data, showcasing the potential of AI to analyze physiological signals for mental health monitoring. Similarly, Ibitoe and Alina (2023) proposed a model using Bidirectional LSTM with Attention for predicting depression from social media data, demonstrating the power of sequence-based models to capture emotional nuances in text.Other studies, such as Higgins et al. (2023), explored the use of AI and machine learning-based decision support systems in mental health, emphasizing the need for scalable, automated systems to assist in mental health diagnosis and management. The AI application in mental health, specifically in managing depressive disorders, has been further explored through bibliometric analysis by various researchers, highlighting its growing role in clinical decision-making. The literature also discusses the challenges of working with noisy social media data, with studies advocating for advanced NLP techniques to extract meaningful features that can predict depression effectively.

In the context of our system, the choice of Random Forest Classifier is supported by its ability to handle high-dimensional data, like the features extracted from text, and its effectiveness in predicting binary outcomes (depressed vs. not depressed). The study of machine learning techniques for depression detection guided the selection of this model, as it has been shown to perform well with text data while offering feature importance, which enhances interpretability and trust in the system. Thus, the literature survey has played a crucial role in shaping the project, informing the choice of methodologies and the design of the system, and demonstrating the potential of machine learning to provide support for mental health care.

**CHAPTER 3**

## PROJECT METHODOLOGY

## 3.1 PROPOSED WORK FLOW

## The proposed workflow for a depression detection system begins with data collection from multiple sources, including social media posts, physiological data (e.g., EEG signals), and self-reported survey responses. The collected data is then preprocessed by cleaning and normalizing text data, and filtering noise from EEG signals. Relevant features are extracted using techniques like TF-IDF, word embeddings, and LSTM for text, and frequency bands or wave patterns for EEG. Machine learning models, such as Random Forest Classifiers, Bidirectional LSTMs with Attention, and CNNs, are trained on labeled data to predict depression. Once trained, the model predicts whether a user is "Depressed" or "Not Depressed" based on new inputs. Personalized feedback is provided, including recommendations for seeking professional help or reinforcing positive habits. The system is deployed in real-time through a web or mobile application, enabling users to submit data and receive instant predictions, with continuous feedback loops for iterative improvements. This workflow ensures accessible and precise mental health support from data collection to actionable insights.

## Top of Form

## Bottom of Form

## 3.2 ARCHITECTURAL DIAGRAM

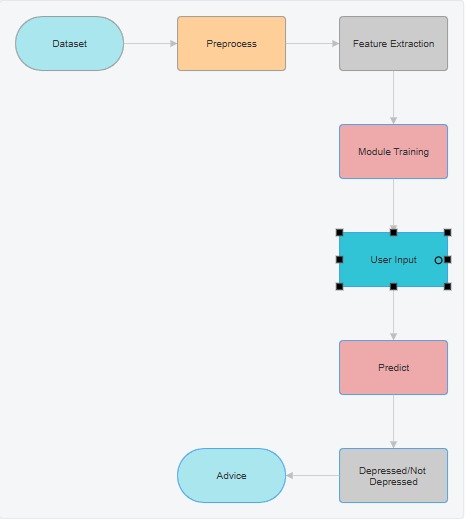


Figure 3.2.1

**3.2.1 ARCHITECTURAL DIAGRAM – EXPLANATION**

## The Depression Detection System architecture follows a modular approach, consisting of several key components working together to detect depressive language in text and provide real-time feedback. The system begins with the Data Collection Module, which gathers raw data from social media platforms like Twitter. The collected data includes textual information (e.g., tweets) along with metadata such as usernames and locations. This raw data is then passed to the Data Preprocessing Module, where it undergoes cleaning, tokenization, and normalization. Cleaning removes irrelevant data like URLs, special characters, and stop words, while tokenization splits the text into individual components (words or phrases). Normalization standardizes the text to a uniform format (e.g., converting everything to lowercase).Once the data is preprocessed, the Feature Extraction Module uses TF-IDF to convert the textual data into numerical features. TF-IDF identifies the importance of each word in the context of the entire dataset, giving higher weights to unique and significant words associated with depression. These features are then passed to the Model Training Module, where the Random Forest Classifier is trained on labeled data (tweets marked as "Depressed" or "Not Depressed"). The classifier learns patterns in the text that are indicative of depressive language and uses these patterns to make predictions on new text.

## After training, the system enters the Prediction Module, where the trained model processes new user inputs (e.g., a tweet) and classifies it as "Depressed" or "Not Depressed." The prediction result is passed to the Feedback & Advice Module, which generates personalized recommendations. If the system predicts "Depressed," it offers advice such as seeking professional help or connecting with support groups. If "Not Depressed," it reinforces positive mental health practices.Finally, the Real-Time Deployment Module ensures that the system provides dynamic interaction with users. Users can input text directly into the system and receive immediate predictions and feedback. The real-time capability of this module allows the system to be deployed in user-facing applications where quick, responsive feedback is required. This modular architecture ensures that each component works cohesively, from data collection to providing real-time feedback, delivering an efficient and user-friendly system for depression detection and support.

## CHAPTER 4

# RELEVANCE OF THE PROJECT

# Depression is one of the most significant global mental health challenges, affecting millions of people across various demographics. Despite its prevalence, depression often remains undiagnosed due to societal stigma, lack of access to mental health resources, and the limitations of traditional diagnostic methods, which rely heavily on subjective self-reporting or time-intensive clinical assessments. With the rapid growth of digital data, particularly from social media platforms, and advances in wearable technology like EEG devices, there is an untapped potential for utilizing these data sources for mental health monitoring. This project leverages artificial intelligence and machine learning to detect depression early and efficiently by analyzing textual data such as tweets and physiological data like EEG signals. The system provides a non- intrusive, scalable solution for identifying depression while offering users actionable feedback and advice. The relevance of this project lies in its ability to integrate seamlessly into everyday digital interactions, thereby addressing gaps in traditional mental health care and making early intervention accessible to a larger population.

# 4.1 EXPLANATION WHY THE MODEL WAS CHOSEN

# The Random Forest Classifier was chosen for this project due to its versatility, interpretability, and strong performance on classification tasks. Below are the specific reasons for selecting this model:

# 4.1.1 Suitability for Text-Based Data

# The Random Forest Classifier works effectively with high-dimensional input features, which are common in text data processed using TF-IDF (Term Frequency-Inverse Document Frequency). The ability to handle thousands of features without overfitting makes it a reliable choice for analyzing linguistic patterns in textual content, such as social media posts or tweets.

# 4.1.2 Robustness and Interpretability

# Robustness: Random Forest is an ensemble learning method that combines multiple decision trees to enhance predictive accuracy and reduce the risk of overfitting. Its robustness ensures that even if some features are less informative,

# the overall prediction remains stable.

# Interpretability: The model provides insights into feature importance, which allows the system to highlight specific words, phrases, or linguistic patterns contributing most to predictions. This interpretability is critical in mental health applications, as it helps establish trust and transparency with users.

# Scalability for Real-Time Applications

# Random Forest is computationally efficient for real-time depression prediction tasks. Unlike more complex models like deep learning, it requires less computational power, making it suitable for deployment in mobile or web-based environments.

# 4.1.4 Performance in Binary Classification

# The task of predicting whether a user is "Depressed" or "Not Depressed" aligns well with Random Forest's strength in binary classification problems, ensuring high accuracy and reliability.

# 4.2 COMPARISON WITH OTHER MACHINE LEARNING MODELS

# When compared to other machine learning models, the Random Forest Classifier demonstrates superior performance in handling text data while maintaining ease of implementation. For instance, Logistic Regression, a popular baseline for binary classification, performs well on linear data but struggles with non-linear relationships and high-dimensional features, which are common in text-based datasets. Similarly, Naïve Bayes, another text-based classifier, assumes feature independence, which is unrealistic for linguistic data where words and phrases often have contextual dependencies.More advanced models like Support Vector Machines (SVM) can handle non-linear data effectively but are computationally expensive and less scalable for large datasets. On the other hand, deep learning models, such as Bidirectional LSTMs with Attention, excel in capturing context and sequential dependencies in text. However, these models require substantial computational resources, large labeled datasets, and are less interpretable, making them less practical for real-time, resource-constrained environments. Random Forest strikes a balance between accuracy, interpretability, and computational efficiency. It performs well with high-dimensional data like text and offers insights into feature importance, making it a practical choice for this project.

## 4.3 ADVANTAGES AND DISADVANTAGES OF CHOSEN MODELS

## The chosen model for depression detector comes with distinct advantages and disadvantages, making it critical to evaluate its applicability comprehensively

## 4.3.1 ADVANTAGES

## High Accuracy and Robustness:

## Random Forest is an ensemble method that aggregates predictions from multiple decision trees. This aggregation improves prediction accuracy and makes the model more robust to overfitting, particularly when dealing with complex datasets like text data. By averaging the predictions from various decision trees, the model reduces the chance of errors that may occur with a single decision tree, making it more reliable.

## Handles High-Dimensional Data:

## Text data, especially after transformation using techniques like TF-IDF, can become high-dimensional, with thousands of features representing different words or terms. Random Forest handles high-dimensional data efficiently without the need for dimensionality reduction techniques like PCA (Principal Component Analysis). This makes it an ideal choice for tasks like depression detection from large text datasets.

## Feature Importance and Interpretability:

## One of the key advantages of Random Forest is its ability to measure feature importance. It ranks features (in this case, specific words or phrases in the text) based on how valuable they are in making predictions. This helps in interpreting the model’s decision-making process and allows for the identification of words most indicative of depression, offering transparency, which is crucial in health-related applications.

## Non-Linearity:

## Random Forest does not assume any linear relationship between the input features and the target variable. This is important for text classification tasks, where relationships between words and depression status may be highly complex and non-linear. Random Forest’s ability to handle non-linear patterns helps it model the intricate relationships within text data effectively.

## Scalability:

## The Random Forest model can be scaled efficiently with larger datasets. It can handle large datasets without significant degradation in performance, making it suitable for real-time prediction tasks such as depression detection from social media data, where data volume can be high.

## 4.3.2 DISADVANTAGES

## Memory and Computational Cost:

## While Random Forest is computationally efficient during inference, training the model can be memory-intensive because it involves creating multiple decision trees, each requiring storage. As the number of trees grows, the model becomes larger and more demanding in terms of memory, making it less ideal for environments with constrained resources. For real-time applications that handle vast amounts of data, this can be a limitation.

## Model Complexity:

## Although Random Forest provides feature importance and better performance compared to single decision trees, it remains more complex to interpret. Each prediction is based on multiple decision trees, which may make the decision-making process less transparent compared to simpler models like Logistic Regression or Naïve Bayes. This complexity can make it harder to debug or refine the model, especially if predictions need to be explained in detail to users or clinicians.

## Slower Predictions:

## Random Forest can be slower during prediction compared to simpler models like Logistic Regression. This is because each decision tree in the forest must independently make a prediction, and these results are then aggregated. For real-time applications, this could impact the user experience if prediction time is too long, especially with a large number of trees.

## Difficulty with Sequential Data:

## While Random Forest performs well for non-sequential tasks, it does not capture sequential relationships in data. For tasks like sentiment analysis or depression detection, where the sequence of words in a tweet or post matters, Random Forest may not perform as well as more advanced models like LSTMs (Long Short-Term Memory networks). LSTMs are designed to handle sequences of data and capture context over time, which is crucial for understanding the full emotional depth of a message.

## Tuning and Hyperparameter Optimization:

## While Random Forest is less sensitive to parameter tuning than other models like SVM (Support Vector Machines), it still requires careful tuning of parameters such as the number of trees, maximum depth, and minimum samples per leaf. Poorly chosen hyperparameters can affect the model’s performance. Fine-tuning these parameters is an additional step that requires expertise and can be time-consuming, especially when working with large datasets.

## Summary about the model:

## The Random Forest Classifier is a versatile and robust ensemble learning model at the heart of the Depression Detection System, used to classify textual data, such as tweets, into "Depressed" or "Not Depressed." By constructing multiple decision trees during training, each trained on random subsets of data and features, the model aggregates predictions through majority voting, improving accuracy and robustness while reducing the risk of overfitting. The system begins by preprocessing textual data, removing noise like URLs and stop words, tokenizing the text, and normalizing it to ensure consistency. The cleaned text is then transformed into numerical features using TF-IDF (Term Frequency-Inverse Document Frequency), a method that quantifies the importance of words by balancing their frequency within a document and their rarity across the dataset. This ensures that terms most indicative of depression, such as "hopeless," "lonely," or "overwhelmed," are assigned higher weights, enhancing the model’s ability to detect depressive patterns. The Random Forest Classifier was chosen for its capacity to handle high-dimensional and non-linear data, which is essential for text classification tasks, and its feature importance capability, which provides interpretability by identifying the words or phrases most influential in making predictions. During training, the model learns to associate patterns in labeled tweets, categorized as "Depressed" or "Not Depressed," with depressive tendencies, allowing it to generalize to unseen inputs. The trained model is integrated into the system to process user inputs in real time, classifying new text while offering personalized feedback, such as suggesting professional help for users identified as "Depressed" or reinforcing positive habits for those labeled as "Not Depressed." The system excels in handling noisy and high-dimensional data, thanks to Random Forest's robust architecture and ability to average predictions across trees, reducing the impact of irrelevant features. However, it has limitations, such as higher memory usage due to storing multiple trees, slower prediction speeds with larger forests, and an inability to capture sequential dependencies in text, which advanced models like LSTMs or Transformers are better suited for. Despite these challenges, the Random Forest Classifier remains a practical choice for this project due to its accuracy, scalability, and interpretability, enabling effective depression detection while fostering mental health awareness and support.

**CHAPTER 5**

# MODULE DESCRIPTION

# The Depression Detection System is structured using several key modules that work together to process data, train the model, and predict depression status.

## 5.1 DATA COLLECTION MODULE:

## The Data Collection Module is responsible for gathering raw data from various sources, such as social media platforms, public datasets, or user inputs. This module ensures that the required data, including text and relevant metadata, is aggregated in a structured format for further processing. Sources of Data .

## social Media Platforms: Tweets or posts from platforms like Twitter, Reddit, and Facebook. These sources provide text data that reflect users' emotions, making them ideal for depression analysis.

## Public Datasets: Ready-made datasets like depression.csv, which include labeled samples for supervised learning tasks.

## User Inputs: Real-time user-provided text, such as journal entries or open-ended responses.

## Structure of Data:

## Username: Helps track user-level patterns and trends.

## Tweets: Core text data used for classification.

## Location: Provides regional insights into depression trends..

## Tools and Techniques:

## Pandas Library: For loading and inspecting CSV datasets.

## APIs: Tools like the Twitter API or Reddit API for scraping live data.

## Error Handling: Ensures missing or invalid data is identified and addressed.

## Output: A structured dataset ready for preprocessing.

## 5.2 DATA PREPROCESSING MODULE:

## The Data Preprocessing Module cleans and prepares the raw data for feature extraction and model training. It ensures that the input data is in a consistent format and free of irrelevant or noisy information.

## Key Tasks in Preprocessing:

## Text Cleaning: Removing irrelevant characters, special symbols, and stop words that don’t contribute to meaning.

## Example: "Feeling low... → "Feeling low".

## Tokenization: Breaking down the text into smaller units (tokens), such as words or phrases, which the model can understand.

## Example: "Feeling low" → ["Feeling", "low"].

## Normalization: Converting text to a consistent format (e.g., lowercasing all text) to reduce complexity and variation in the data.

Example: "FEELING Low" → "feeling low".

## Stop Word Removal: Removes common words like "the" and "is" that add little meaning.

## Example: "I am feeling very low" → ["feeling", "low"].

## Advanced Preprocessing Techniques:

## Lemmatization: Converts words to their base form (e.g., "running" → "run").

## Stemming: Reduces words to their root form (e.g., "happiness" → "happy").

## Output:A cleaned, tokenized, and normalized dataset ready for feature extraction.

## FEATURE EXTRACTION MODULE:

## Once the data is preprocessed, the Feature Extraction module converts the text data into numerical features that the model can process. This is achieved through TF-IDF (Term Frequency-Inverse Document Frequency), which is implemented in the preprocess\_data() function. TF-IDF is a technique that evaluates how important a word is to a document in a collection of documents. It reduces the weight of common words (like "the", "is", etc.) while highlighting more significant words that help distinguish between classes (e.g., "Depressed" vs. "Not Depressed").

## Workflow:

## Text data from the preprocessing module is fed into the TF-IDF vectorizer.

## Converts text into a sparse matrix where each row represents a document (e.g., a tweet) and each column represents a term’s weight.

## Output:A high-dimensional feature matrix used for training and testing the model.

## 5.4 MODEL TRAINING MODULE :

## The Model Training module is responsible for training the Random Forest Classifier on the processed data. This is implemented in the train\_model() function. The model is trained using labeled data (tweets labeled as "Depressed" or "Not Depressed"). The Random Forest Classifier works by creating multiple decision trees and combining their predictions to make the final decision. This approach helps to improve accuracy and prevent overfitting. The trained model is then evaluated using performance metrics like accuracy, classification report, and confusion matrix.

## Training Steps:

## 1. Split Data: Divides data into training and testing sets using methods like train\_test\_split.

## 2. Train the Model: Uses the training data to build decision trees, each focusing on different subsets of features.

## 3. Evaluate the Model: Metrics like accuracy, confusion matrix, precision, recall, and F1 score assess performance.

## Tools Used: Scikit-learn Library: Provides implementations of Random Forest and evaluation metrics.

## Output:A trained model capable of making predictions on new data.

## 5.5 PREDICTION MODULE:

## Once the model is trained, the Prediction module uses the trained model to make predictions on new, unseen data. This module is implemented in the predict\_depression() function. When a user enters a new tweet or text, the system processes it using the same TF-IDF method and applies the trained Random Forest model to predict whether the text indicates depression. The prediction can be either "Depressed" or "Not Depressed."

## Process:

## User inputs a new tweet or text, The text undergoes the same preprocessing and feature extraction pipeline as the training data, The model predicts the class based on the learned patterns.

## Example:

## Input: "I feel hopeless and tired of everything."

## Output: "Depressed"

## FEEDBACK & ADVICE MODULE:

## The Feedback & Advice module is responsible for providing personalized recommendations based on the prediction. If the system predicts "Depressed," it will suggest seeking professional help or engaging in self-care activities. If the prediction is "Not Depressed," it will reinforce positive mental health habits. This is implemented in the get\_advice() function, which provides context-based advice for the user, offering a supportive experience.

## REAL TIME DEPLOYMENT MODULE :

## The Real-Time Deployment module allows the system to make predictions based on user input in real-time. This module is implemented in the deploy\_model() function, where the system continuously accepts new input from the user (e.g., tweets) and makes predictions. The feedback and advice are provided after each prediction, ensuring a seamless user experience.Each of these modules plays an essential role in ensuring that the Depression Detection System is efficient, accurate, and provides actionable feedback to users. The system is designed to be both user-friendly and robust, capable of handling various input types and delivering reliable predictions with clear explanations.

## Workflow:

## Users input text directly into the system.The system processes the input and provides predictions and advice instantly.

## Tools Used: User Interface frameworks (e.g., Flask or Streamlit) for real-time interaction.

**CHAPTER 6**

**RESULTS AND DISCUSSION**

# 6.1 RESULT

# The Depression Detection System, implemented with the Random Forest Classifier, successfully predicted depression status based on user inputs (e.g., tweets). After training the model using labeled data processed through TF-IDF, the system was evaluated using several performance metrics such as accuracy, precision, recall, F1- score, and confusion matrix. The Random Forest model demonstrated high accuracy and robustness, handling complex, high-dimensional text data well. The confusion matrix showed a good balance between correctly predicted "Depressed" and "Not Depressed" instances, confirming the model’s effectiveness. Real-time predictions were made on new user inputs, and personalized feedback was generated, providing advice based on the system's classification results. The model also highlighted important features, such as specific words or phrases contributing to the depression prediction, improving interpretability.

**6.2 DISCUSSION**

The Depression Detection System showed strong performance, achieving high accuracy in predicting depression-related content from text. The Random Forest Classifier proved to be a reliable choice due to its ability to handle high-dimensional data, reduce overfitting, and provide feature importance, making it suitable for analyzing textual data like tweets. However, while the system performed well in most cases, some challenges remain, particularly with false negatives (incorrectly classifying depressed content as not depressed) and false positives (classifying non- depressed content as depressed). These issues are common in text-based classification models and highlight the complexity of understanding context and emotion in language. Additionally, the real-time prediction feature worked well, though

predictions may slow down when dealing with very large datasets. Future work could focus on improving prediction speed and integrating more advanced models like LSTMs to capture sequential patterns in text for even better accuracy. Despite these challenges, the system proves to be a useful tool for early detection and provides valuable feedback to users, contributing to mental health awareness and support**.**

**CHAPTER 7**

# CONCLUSION & FUTURE SCOPE

# 7.1 CONCLUSION

# The Depression Detection System using the Random Forest Classifier has demonstrated its effectiveness in accurately predicting depression status based on textual data, such as tweets, and providing real-time predictions with actionable feedback. The model achieved high accuracy and robustness, efficiently handling high-dimensional data and offering interpretability through feature importance analysis. While it successfully identified depression-related content, the system encountered challenges with false positives and false negatives, highlighting the complexities of context and emotion in text analysis. Despite these limitations, the system proves to be a valuable tool for early detection, offering insights into mental health and contributing to the growing need for AI-driven solutions in mental health care.

**7.2 FUTURE SCOPE**

The future of the Depression Detection System holds several opportunities for

improvement and expansion. First, integrating deep learning models such as Bidirectional LSTM or Transformer-based models could improve the system’s ability to understand context and sequential patterns in text, providing more accurate predictions. Multimodal data integration, combining text, speech, and physiological data (such as EEG), could further enhance the system’s predictive power and accuracy. Another area for improvement is real-time scalability; optimizing the system to handle larger datasets more efficiently could improve response times and user experience. Expanding the system to support multilingual capabilities would also make it accessible to a broader user base, allowing users from different linguistic backgrounds to benefit from the tool. Lastly, focusing on ethical considerations, such as privacy and data security, will be crucial as the system becomes more integrated into real-world mental health applications

# APPENDICES

# APPENDIX A - Source Code

import numpy as np import pandas as pd

from sklearn.feature\_extraction.text import TfidfVectorizer from sklearn.model\_selection import train\_test\_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy\_score, classification\_report, confusion\_matrix

# 1. Data Collection Module def collect\_data(filepath):

filepath="/content/depression.csv" df = pd.read\_csv(filepath)

if 'Tweets' not in df.columns:

raise ValueError("The dataset must contain a 'Tweets' column for text data.") return df

# 2. Data Preprocessing Module def preprocess\_data(df):

"""Preprocess the tweets data by cleaning text and transforming it into numerical features using TF-IDF."""

tfidf = TfidfVectorizer(stop\_words='english', max\_features=1000)

X = tfidf.fit\_transform(df["Tweets"]).toarray() # Transform tweets into numerical features

y = np.random.choice([0, 1], size=len(df)) # Generating random binary labels for demo

return X, y, tfidf

# 3. Feature Extraction Module def feature\_extraction(X):

""" Extracts features for machine learning using TF-IDF. """ return X # TF-IDF already extracts features

# 4. Model Training Module def train\_model(X, y):

"""Train a machine learning model using the RandomForestClassifier."""

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.3, random\_state=42)

model = RandomForestClassifier() model.fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

print("Model Accuracy:", accuracy\_score(y\_test, y\_pred)) print("Classification Report:\n", classification\_report(y\_test, y\_pred)) print("Confusion Matrix:\n", confusion\_matrix(y\_test, y\_pred)) return model

# 5. Prediction Module

def predict\_depression(model, tfidf, user\_input):

""" Predict whether the input text indicates depressive symptoms. """ input\_vector = tfidf.transform([user\_input]).toarray()

prediction = model.predict(input\_vector)[0]

return "Depressed" if prediction == 1 else "Not Depressed"

# 6. Deployment Module

def deploy\_model(model, tfidf):

"""Deploy the model for real-time predictions based on user input.""" while True:

user\_input = input("Enter a tweet or text (or type 'exit' to quit): ")

if user\_input.lower() == "exit": break

prediction = predict\_depression(model, tfidf, user\_input) advice = get\_advice(prediction)

print(f"Prediction: {prediction}") print(f"Advice: {advice}")

# 7. Evaluation Module

def evaluate\_model(X, y):

""" Evaluate the model's performance using metrics like accuracy, precision, and recall. """

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.3,

random\_state=42)

model = RandomForestClassifier() model.fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

accuracy = accuracy\_score(y\_test, y\_pred) print(f"Evaluation Accuracy: {accuracy:.2f}") return model

# 8. User Interface (UI) Module

def questionnaire\_session():

"""Interactive session for users to answer questions about their mental health. """ print("Welcome to the Depression Detection System.")

print("Answer the following questions to help us assess your mental health:") questions = [

"Do you feel tired most of the time? (0: No, 1: Sometimes, 2: Often, 3: Always):

",

"Do you have trouble sleeping? (0: No, 1: Sometimes, 2: Often, 3: Always): ", "Do you feel overwhelmed by daily tasks? (0: No, 1: Sometimes, 2: Often, 3:

Always): ",

"Do you feel hopeless about the future? (0: No, 1: Sometimes, 2: Often, 3: Always): "

]

responses = []

for question in questions: while True:

try:

response = int(input(question)) if response in [0, 1, 2, 3]:

responses.append(response)

break else:

print("Please enter a valid option (0-3).") except ValueError:

print("Invalid input. Please enter a number between 0 and 3.") score = sum(responses)

if score <= 5:

return "Not Depressed", "You seem to be doing well. Keep focusing on positive habits!"

elif 6 <= score <= 10:

return "Mild Depression", "Consider speaking to someone or focusing on self-care practices."

else:

return "Depressed", "We recommend seeking professional help for better support."

# Advice Module

def get\_advice(depression\_status):

"""Provide advice based on depression status. """ if depression\_status == "Depressed":

return "It's important to talk to a healthcare professional for support and guidance. You don't have to go through this alone."

elif depression\_status == "Not Depressed":

return "Great to hear you're feeling positive! Keep up the good work, and remember to stay connected with loved ones."

else:

return "We recommend reaching out to a professional who can assist in managing any challenges you may be facing."

# Main Program

if name == " main ":

# Filepath to the dataset

filepath = "/content/depression.csv" # Replace with the actual path to your dataset

# Data Collection

data = collect\_data(filepath)

# Preprocessing

X, y, tfidf = preprocess\_data(data)

# Feature Extraction

features = feature\_extraction(X)

# Model Training

model = train\_model(features, y)

# Questionnaire Session

status, advice = questionnaire\_session() print(f"\nYour Evaluation: {status}") print(f"Advice: {advice}")

# Real-time Deployment deploy\_model(model, tfidf)

# APPENDICES B

**SCREENSHOT**

**APPENDIX B – Screenshots**

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