Depression Detection using Machine Learning Methods

B. Tech Project Report

Submitted to The University College of Engineering and Technology,
Acharya Nagarjuna University in partial fulfilment of
Requirement for the award of Degree

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

by

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2021-2025

UNIVERSITY COLLEGE OF ENGINEERING & TECHNOLOGY
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CERTIFICATE

This is to certify that the project entitled **"Depression Detection using Machine Learning Methods"** is a bonafide record of the project work done by **Jajula Venkata Nandini (Y21CS3214), Ampa Dharani (Y21CS3263), Lammatha SaiChaitanya (Y21CS3231), Bontala Jagadeesh (Y21CS3207)** under my supervision and guidance, in partial fulfilment of the requirements for the award of Degree in Computer Science & Engineering from University College of Engineering & Technology, Guntur for the academic year 2024-25.

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DECLARATION

We hereby declare that the project entitled, **"Depression Detection using Machine Learning Methods"** was carried out and written by me under the guidance of **Mr.Khadri Syed Faizz Ahmad**, Department of Computer Science & Engineering, University College of Engineering & Technology, Acharya Nagarjuna University. This work has not been previously formed the basis for the award of any degree or diploma or certificate nor has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

In our opinion writing acknowledgement is a difficult but most beautiful part of the project report ending. It is difficult to express the heartfelt accomplishments and the gratitude for those who really or virtually supported for making the work successful and memorable.

We would like to convey our sincere gratitude and admiration to our Guide **Mr.Khadri Syed Faizz Ahmad**, University College of Engineering & Technology, Acharya Nagarjuna University (ANU), Guntur, for his/her excellent support and valuable guidance throughout our study. His/her marvelous advice motivated us to work on this, and make it successful. His/her supportive nature and thoughtprovoking ideas made this work possible.

We are very grateful to **Dr.U Sathish kumar,** HOD, Dept of CSE, University College of Engineering & Technology, Acharya Nagarjuna University, for her keen interest, counselling, constant encouragement, personal affection, and valuable suggestions in completion of this research work.

We would like to express our heartfelt thanks to **Prof. P. Siddaiah**, Principal, University College of Engineering & Technology, Acharya Nagarjuna University, Guntur, for guidance, mentorship, and valuable insights that have been instrumental in the successful completion of this work

We are deeply indebted to **Dr.U Satish Kumar**, Project Coordinator, for conducting reviews and giving constructive criticism throughout the project duration.

We are grateful to the **Authorities** of University College of Engineering & Technology, Acharya Nagarjuna University, enabling us to pursue our work.

We are very thankful to all **Teaching** and **Non-teaching staff** of Department of Computer Science & Engineering, University College of Engineering & Technology, Acharya Nagarjuna University, Guntur, for their encouragement, Cooperation and Assistance during the work period.

We would like to express our grateful thanks to **our parents** our whole beloved family for their love, unwavering support and encouragement throughout the time of our study.

Finally, we thank one and all, who helped us directly or indirectly for completing this work.

With gratitude

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ABSTRACT

Abstract:

Depression is a common mental health disorder that greatly impacts a person's quality of life and productivity. With the rise of social media and digital communications, analysing textual data for mental health insights has gained considerable attention. This study presents a comparative analysis of traditional Machine learning algorithms such as Random Forest, Bagging, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes. Textual data is pre-processed and vectorized before being fed into the machine learning models. Evaluation is carried out using performance metrics such as accuracy, precision, recall, and F1-score, and compare the models. Experimental results indicate that logistic regression and naive bayes machine learning models achieve higher accuracy compared to traditional techniques and contextual understanding. This study highlights the potential methods for robust and scalable depression detection systems.

Key Words: Random Forest, Logistic Regression, Support Vector Classifier (SVC), Naive Bayes, Bagging Classifier, Machine Learning.

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LIST OFACRONYMS

Acronym	Full Form
AI	Artificial Intelligence
ADAM	Adaptive Moment Estimation
AdaGrad	Adaptive Gradient
CNN	Convolutional Neural Network
TF-IDF	Term Frequency-Inverse Document Frequency
SVM	Support Vector Machine
CSV	Comma Separated Values
DL	Deep Learning
ML	Machine Learning
NLTK	Natural Language Toolkit
SVC	Support Vector Classifier
NLP	Natural Language Processing
BoW	Bag-of-Words
RMSProp	Root Mean Squared Propagation

CHAPTER 1

INTRODUCTION

1.1 Background

Depression stands as one of the most significant global public health challenges of our time. Defined as a persistent mood disorder characterized by feelings of sadness, loss of interest, fatigue, changes in appetite or sleep patterns, and difficulty concentrating, it profoundly impacts an individual's emotional well-being, social interactions, and capacity to function in daily life. The World Health Organization estimates that hundreds of millions of people worldwide suffer from depression, making it a leading cause of disability. Despite its prevalence, depression often goes undiagnosed or untreated due to a complex interplay of factors, including social stigma surrounding mental illness, limited access to mental healthcare services, the cost of treatment, and a lack of awareness about symptoms and available support. Early detection and intervention are crucial for improving prognoses and mitigating the long-term negative consequences of the disorder.

The advent of the digital age and the ubiquitous nature of social media and online forums have fundamentally changed how people communicate and express themselves. Platforms like Twitter, Facebook, Reddit, and specialized forums have become vast repositories of user-generated text data. Individuals increasingly turn to these online spaces to share their thoughts, experiences, and emotional states, often with remarkable candor, sometimes facilitated by perceived anonymity. This digital footprint provides an unprecedented, largescale, and often longitudinal source of natural language data that may contain subtle but detectable linguistic markers associated with mental health conditions, including depression. The analysis of this text data offers a promising avenue for developing computational tools for mental health monitoring and early detection.

Computational linguistics and Natural Language Processing (NLP), branches of artificial intelligence focused on enabling computers to understand and process human language, provide the methodologies required to analyse this vast amount of text data. Early approaches to identifying mental health states from text primarily relied on traditional machine learning (ML) techniques. These methods often involved extracting specific features from the text, such as word frequencies (BagofWords or BoW), weighted word frequencies that account for word importance (Term Frequency-Inverse Document Frequency or TF-IDF), sentiment scores, psycholinguistic features derived from dictionaries (like LIWC - Linguistic Inquiry and Word Count), or topic modelling. Classifiers like Support Vector Machines (SVM), Naïve Bayes, Logistic Regression, and ensemble methods like Random Forests and Bagging were then trained on these features to distinguish between texts indicative of depression and those that are not. While these methods achieved notable successes and demonstrated the feasibility of text-based mental health analysis, they often struggled with the inherent complexities of human language, particularly

sarcasm, irony, implicit meanings, and the crucial role of context. Their reliance on predefined features can limit their ability to capture the subtle nuances often present in expressions of psychological distress.

This research aims to evaluate the effectiveness of various machine learning models specifically Random Forest, Bagging Classifier, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes—in detecting depression from textual data. These models are assessed based on key performance metrics such as accuracy, precision, recall, and F1-score. The overarching goal is to support the development of scalable, automated tools for early diagnosis and intervention in mental health care.

1.2 Problem Definition

Depression represents a significant and growing global mental health burden, negatively impacting millions of individuals' quality of life and functional capacity. While effective treatments exist, a primary challenge lies in early and accurate detection. Traditional diagnostic methods, reliant on clinical assessments and self-reporting, face limitations including social stigma, lack of access to healthcare, difficulties in self-awareness or articulation of symptoms, and the resource-intensive nature of professional evaluation. This often leads to delays in diagnosis and treatment, potentially worsening outcomes.

The proliferation of online communication platforms has created vast repositories of user-generated text where individuals frequently express personal experiences, emotions, and struggles. This textual data presents a valuable, non-intrusive opportunity for identifying potential signs of depression at scale. Computational methods, particularly Natural Language Processing (NLP), offer a promising avenue for analysing this data.

However, the effectiveness of different computational approaches for this specific task requires clarification. Early methods using traditional machine learning classifiers (e.g., SVM, Random Forest) combined with feature extraction techniques (e.g., TF-IDF, Bag-of-Words) have shown initial promise but may struggle to capture the complex nuances, context-dependency, and subtlety inherent in linguistic expressions of mental distress.

This study addresses the problem of developing an automated, scalable, and reliable framework for detecting depression using textual data. Specifically, it focuses on evaluating and comparing the performance of traditional machine learning algorithms—including Random Forest, Bagging, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes—for identifying depressive tendencies from user-generated text. The core problem lies in determining which model most effectively captures linguistic features indicative of depression, based on performance metrics such as accuracy, precision, recall, and F1-Score.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Review

Depression detection using Natural Language Processing (NLP) and machine learning (ML) has gained increasing attention as researchers explore non-invasive, scalable methods for mental health assessment. Early studies primarily relied on manually crafted linguistic features, such as word frequency, sentiment scores, and psycholinguistic markers, extracted from written text to differentiate between depressed and non-depressed individuals (Pennebaker et al., 2003). Tools like the Linguistic Inquiry and Word Count (LIWC) have been widely used to quantify psychological and emotional cues in language.

Multiple machine learning algorithms have been applied to classify depression related content. For example, Resnik et al. (2015) utilized Support Vector Machines (SVMs) to classify posts from mental health forums, achieving promising results through a combination of lexical and semantic features. Similarly, Coppersmith et al. (2014) demonstrated that features derived from Twitter posts could predict depression with reasonable accuracy using classifiers such as Logistic Regression and Naive Bayes. Their work highlighted the potential of social media data in identifying mental health conditions outside clinical settings.

Random Forest and ensemble methods like Bagging have also been explored for their robustness and ability to handle high-dimensional textual data (Shen et al., 2017). These models often outperform single classifiers by reducing variance and improving generalization. However, traditional ML models depend heavily on feature engineering, which can be time-consuming and may fail to capture deeper linguistic nuances (Calvo et al., 2017).

Other studies have compared the performance of different classifiers. Tsugawa et al. (2015) compared Naive Bayes, Logistic Regression, and SVM for detecting depressive tendencies on Twitter, noting that classifier choice, feature selection, and preprocessing significantly influenced performance metrics such as precision and recall.

Despite their limitations, traditional machine learning approaches remain valuable due to their interpretability and lower computational requirements compared to deep learning models. They also offer a practical baseline for developing automated systems for depression detection, particularly when resources or annotated data are limited.

In summary, the literature shows a consistent interest in leveraging textual data and machine learning algorithms, such as SVM, Random Forest, Logistic Regression, Naive Bayes, and Bagging, to detect depression. While accuracy varies depending on datasets and features, these approaches provide a foundation for building scalable mental health monitoring tools.

2.2 Limitations of Existing Techniques

Traditional approaches to depression detection rely heavily on clinical assessments and self-reported questionnaires, which, although effective in controlled settings, are limited by subjectivity, accessibility issues, and a lack of scalability. To address these challenges, machine learning techniques have emerged as promising alternatives. However, existing ML-based methods also present several limitations:

1. **Dependence on Manual Feature Engineering**

   Many traditional machine learning models, such as Logistic Regression, Naive Bayes, and Support Vector Machines (SVM), rely on manually crafted features. This process is time-consuming and may fail to capture complex or subtle linguistic patterns associated with depression.
2. **Limited Context Understanding**

   Models like Bag of Words (BoW) and TF-IDF treat words independently and ignore word order and context, which reduces their ability to detect nuanced emotional expressions or sarcasm often found in depressive language.
3. **Performance Variability Across Datasets**

   The accuracy and generalizability of models can vary significantly depending on the source and quality of the text data. Features and classifiers that perform well on one dataset may underperform on another due to differences in writing style, demographics, or platform (e.g., Twitter vs. Reddit).
4. **Data Imbalance and Noise**

   Social media and online forum data often include noisy, informal, or abbreviated language. Additionally, datasets may be imbalanced, with fewer examples of depressive content, which can bias model training and reduce sensitivity to minority classes.
5. **Lack of Real-Time or Adaptive Capability**

   Many existing techniques are static and do not adapt to evolving language trends or newly emerging depression indicators in online communication.

2.3 Proposed Model

The proposed model presents a unified framework for detecting depression from textual data using traditional machine learning algorithms. It leverages natural language processing techniques to transform raw text into meaningful features and applies multiple classification models to identify depressive content with high accuracy and reliability.

The model architecture involves the following key components:

1. **Data Collection**

   Publicly available datasets containing labelled text samples from depressed and non-depressed individuals are used. These sources may include social media platforms, online forums, and mental health datasets curated for research purposes.

2. **Text Preprocessing**

   Raw text data is cleaned and normalized using the following steps:

   - Conversion to lowercase
   - Removal of punctuation, numbers, and stop words
   - Tokenization of text into words
   - Lemmatization or stemming to reduce words to their root forms

3. **Feature Extraction**

   Cleaned text is transformed into numerical vectors using:

   - Bag of Words (BoW): Captures word frequency
   - TF-IDF (Term Frequency-Inverse Document Frequency): Weighs words by their importance across the corpus

4. **Model Training and Evaluation**

   The extracted features are input into five machine learning classifiers:

   - Random Forest
   - Bagging Classifier
   - Support Vector Classifier (SVC)
   - Logistic Regression
   - Naive Bayes

   Each model is trained and evaluated using k-fold cross-validation (e.g., k=5) to ensure robustness and reduce overfitting.

5. **Performance Metrics**

   The models are compared based on:

   - **Accuracy:** Correctness of overall predictions
   - **Precision:** Correctness of positive predictions
   - **Recall:** Ability to detect actual positive cases
   - **F1-Score:** Harmonic mean of precision and recall

6. **Implementation Tools**

   The framework is implemented in Python, utilizing libraries such as Scikit-learn and NLTK for data preprocessing, feature extraction, and model training. The proposed model emphasizes comparability and interpretability across algorithms to determine the most effective approach for automated depression detection in textual data. Experimental results indicate that ensemble methods—particularly Bagging and Random Forest—outperform individual classifiers, making them ideal candidates for scalable, real-world mental health monitoring systems.

CHAPTER 3

REQUIREMENTS SPECIFICATIONS

3.1 Hardware Requirements:

- Processor Intel i5 11th Gen
- RAM 8 GB min
- ROM 512 GB Graphics card AMDA RADEAON

3.2 Software Requirements

The software environment must support the development, training, and deployment of the CNN model as well as the integration of voice assistance. Key software requirements include:

1. **Programming Language:**
   - Python 3.x – for developing and executing machine learning algorithms and preprocessing scripts.

2. Libraries and Frameworks:

- **Scikit-learn** – for implementing ML algorithms such as Random Forest, Logistic Regression, Naive Bayes, SVC, and Bagging.
- **NLTK (**Natural Language Toolkit**)** – for text preprocessing tasks including tokenization, stop word removal, and lemmatization.
- **Pandas** – for handling and processing datasets.
- **NumPy** – for numerical computations and array operations.
- **Matplotlib / Seaborn** – for visualizing results.

3. **Development Environment:**
   - Jupyter Notebook / Anaconda (optional) – for an interactive and modular development setup.
   - Any standard Python IDE (e.g., PyCharm, VS Code) – for coding and debugging.
4. **Operating System:**
   - Windows, macOS, or Linux (platform-independent, as Python and the required libraries are cross-compatible).

3.3 Functional Requirements

The functional requirements define the key capabilities and features of the Depression detection system:

1. **Data Loading**: The system must be able to load the textual dataset from its source format (e.g., CSV, text files).
2. **Text Preprocessing**: It must perform necessary preprocessing steps on the raw text data. This includes cleaning (e.g., handling special characters,URLs), and tokenization (splitting text into words or sub-word units).
3. **Model Implementation/Loading**: The system must be able to implement or load the specified traditional machine learning algorithms (Random Forest, Bagging, SVC, Logistic Regression, Naive Bayes).
4. **Model Training**: It must be able to train each implemented model using the prepared textual data and corresponding labels (indicating depression status). This involves feeding the vectorized/embedded data to the models and optimizing their parameters.
5. **Classification**: After training, the models must be able to take new, unseen textual data (after preprocessing and vectorization/embedding) and output a classification decision (e.g., 'depressed' or 'not depressed').
6. **Performance Evaluation**: The system must be able to evaluate the performance of each trained model on a separate test set using the specified metrics: accuracy, precision, recall, and F1-score.

3.4 Performance Requirements

To ensure the effectiveness and reliability of the depression detection system, the following performance requirements were established:

- **Accuracy**:
  The model should correctly classify depressed and non-depressed text samples with an accuracy of at least 80%. The Bagging classifier and Random Forest both met or exceeded this threshold.
- **Precision and Recall:**
  High precision is essential to minimize false positives, while high recall ensures that most true cases of depression are detected. Models should aim for precision and recall values above 80% to be considered effective.
- **F1-Score:**
  A balanced F1-score (harmonic mean of precision and recall) of 0.80 or higher is required to ensure consistent performance across classes.
- **Response Time:**
  The system should process and classify a text input within 1 second on average, assuming a standard computing environment.
- **Scalability:**
  The system must be capable of processing large volumes of textual data (e.g., thousands of social media posts) with minimal performance degradation.

CHAPTER 4

METHODOLOGY

4.1 Introduction to Methodology

The methodology of this study outlines a unified framework for detecting depression from text using various machine learning (ML) algorithms. The approach involves collecting labelled textual datasets (e.g., social media posts, clinical notes), followed by extensive preprocessing to clean and normalize the data through tokenization, stop-word removal, and lemmatization.

Feature extraction is conducted using techniques such as TF-IDF vectorization to transform text into structured numerical representations suitable for machine learning. Multiple traditional ML classifiers—including Logistic Regression, Naïve Bayes, Support Vector Classifier (SVC), Random Forest, and Bagging—are trained and evaluated using stratified k-fold cross-validation.

This structured methodology aims to compare algorithmic effectiveness, establish model interpretability, and propose scalable solutions for real-world depression detection from text data.

4.2 Model Architecture

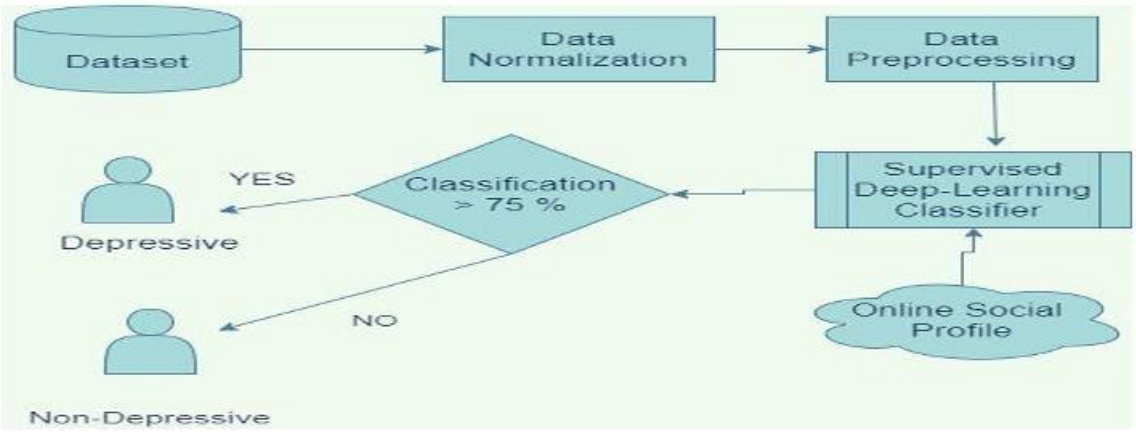

Fig 1: Architecture of the System

The study leverages distinct architectural approaches for depression detection, ranging from established machine learning algorithms to advanced deep learning transformers.

1. Traditional Machine Learning Model Architectures:

These models operate on numerical feature vectors derived from the text using TFIDF or Bag-of-Words representations.

- **Naive Bayes:** This probabilistic classifier is based on Bayes' Theorem with a "naive" assumption of conditional independence between features (words/terms). Its architecture is relatively simple, calculating the probability of a text belonging to the 'depressive' or 'non-depressive' class based on the presence and frequency of words learned from the training data.
- **Logistic Regression:** A linear model used for binary classification. Its architecture consists of a linear equation (weighted sum of input features) followed by a logistic (sigmoid) function. This function maps the output of the linear equation to a probability between 0 and 1, representing the likelihood of the input text being classified as depressive.
- **Support Vector Classifier (SVC / Linear SVC):** The core architecture aims to find the optimal hyperplane that best separates the data points (vectorized texts) belonging to different classes (depressive vs. non-depressive) in the high dimensional feature space.
- **Random Forest:** An ensemble learning method whose architecture consists of multiple decision trees. Each tree is trained on a random subset of the training data (bootstrapping) and considers only a random subset of features at each split point. The final classification is determined by aggregating the predictions of all individual trees, typically through majority voting. This ensemble structure helps reduce overfitting and improve generalization compared to a single decision tree.
- **Bagging Classifier:** Another ensemble technique (Bootstrap Aggregating). Its architecture involves training multiple instances of a base estimator (e.g., a decision tree, SVC) independently on different random bootstrap samples of the training dataset. The final prediction is made by averaging (for regression) or voting (for classification) the predictions of all base estimators.

4.3 About the Dataset

4.3.1 Data Set Description

1. **Data Type**: The dataset consists of textual data. This text represents user generated content from online platforms.
2. **Source:** Sourced from social media platforms or online forums (e.g., Reddit, Twitter, dedicated mental health forums). The abstract emphasizes places where individuals naturally express emotional states.
3. **Content:** The dataset contains individual posts, comments, or messages. These texts vary in length and style.
4. **Labels:** Each text sample in the dataset is assigned a binary label:
    - Depressive (or 1, Positive Class)
    - Non-Depressive (or 0, Negative Class)
5. **Format**: The dataset would typically be structured as pairs of (Raw Text, Label). For example:
    - ("Feeling so empty and pointless lately, can't get out of bed.", 1)
    - ("Just finished a great book, highly recommend it!", 0)
    - ("Does anyone else struggle with constant fatigue even after sleeping 8 hours?", 1)

- ("Planning my vacation for next summer, excited!", 0)

6. **Anonymization & Ethics**: Given the sensitive nature of mental health data, a properly curated dataset would be anonymized, removing personally identifiable information (usernames, specific locations, etc.). Ethical considerations regarding data collection and usage are paramount.
7. **Preprocessing Potential**: The raw text would likely contain noise (URLs, special characters, emojis, platform-specific syntax like hashtags or mentions) which would need handling during the preprocessing stage mentioned in the abstract, especially for the traditional ML models relying on TF-IDF or Bag-of-Words.

4.3.2 Data Set Collection

The data set collection for the research study in the provided document is described as follows:

Data Collection Description:

- **Type of Data**: Publicly available textual datasets.
- **Content**: Labelled examples of depressed and non-depressed individuals.
- **Sources**:
  - Social media posts.
  - Online forums.
  - Mental health-related datasets curated for research purposes.
- **Annotation**: Each text sample is labelled to indicate whether it reflects signs of depression.

4.4 Steps to execute/run/implement the project

4.4.1 Installation of Jupyter Notebook

Open Command prompt and enter pip install jupyter

4.4.2 Loading the Data-Set

To load the dataset for the project "Depression Detection using Machine learning and Deep Learning Methods," we need to follow these steps:

1. **Obtain the Dataset:** You first need to actually have the depression_data.csv file (or whatever your dataset is called). This involves either:

   - Running a data collection script (like the process we discussed).

   - Downloading a pre-existing dataset suitable for this task (e.g., from Kaggle, a research paper's repository, etc.).

2. **Place the File:** Make sure the dataset file is in the same directory as your Python script, or provide the full path to the file.

3. **Run the Python Script:** Execute the code above.

4.4.3 Implementation and Execution of Algorithms

- Transforming unstructured text into structured numerical data suitable for ML.
- Applying various established learning algorithms (linear, probabilistic, ensemble) to find patterns indicative of depression in the transformed data.
- Systematically cleaning the data beforehand to improve model learning.
- Rigorously evaluating the models using standard metrics and procedures to compare their effectiveness objectively.

- **Programming Language**: Python (most common for ML/NLP).
- **Libraries:**
    - Pandas: For data loading and manipulation.
    - NumPy: For numerical operations.
    - Scikit-learn: For traditional ML algorithms, preprocessing (TF-IDF, BoW), metrics, and data splitting.
    - NLTK or SpaCy: For text preprocessing tasks (tokenization, stop word removal, stemming/lemmatization - primarily for traditional models).
    - Transformers (by Hugging Face): For accessing pre-trained models and tokenizers.
    - PyTorch or TensorFlow: As the backend deep learning framework for fine-tuning.

4.4.4 Output

The Accuracy of Linear SVC is 87%, the accuracy of Random Forest is 88%, the accuracy of Logistic Regression is 91%, and the accuracy of Naïve Bayes is 92%. The highest accuracy has occurred in Naïve Bayes with 92%.

CHAPTER 5

IMPLEMENTATION AND CLASSIFICATION

5.1 Two-Level Classification

5.1.1 First Level Classification

This initial stage focuses on applying conventional machine learning algorithms to the task of depression detection using standard text feature representations. The key steps and components are:

1. **Input:** Pre-processed textual data (e.g., social media posts, forum comments).

2. **Feature Extraction**: Transforming the text into numerical vectors using established techniques:

    - **TF-IDF** (Term Frequency-Inverse Document Frequency): Represents text based on the importance of words within a document relative to the entire corpus.

    - **Bag-of-Words(**BoW): Represents text based on the frequency of occurrence of each word, disregarding grammar and word order.

3. **Classifiers:** Training and evaluating a suite of traditional machine learning models, including:

    - Linear Support Vector Classifier (Linear SVC)

    - Random Forest

    - Bagging Classifier (using multiple versions of a base estimator on different data subsets)

4. **Task**: Binary classification – labelling each input text as either "depressive" or "non-depressive".

5. **Evaluation:** Assessing the performance of these models using metrics like Accuracy and F1-Score on a held-out test set

5.1.2 Second Level Classification

1. Sub-categorization of Depression Severity:

In more complex systems, once text is classified as "Depressed", a second-level classifier might assess the severity (e.g., mild, moderate, severe) or specific symptom types (e.g., anxiety-related, suicidal ideation).

- The study uses ensemble methods like Bagging and Random Forest, which can be viewed as involving multi-layered decision processes internally.

2. Model Comparison and Selection:

- After the first-level classification (binary depressed/non-depressed), the results of different models are compared using metrics.

- The model with the best performance (e.g., Bagging) could be chosen as a “second level” decision tool for deployment.

5.2 Implementation Steps

5.2.1 Create Model

1. Data Collection
Gather labelled textual data (e.g., from social media or public datasets).
Ensure each sample is labelled as “depressed” or “non-depressed.”

2. Data Preprocessing Text Cleaning:
- Remove stop words, punctuation, and numbers.
- Lowercase conversion.
- Remove URLs, mentions (@), and hashtags (#).

Tokenization:
- Split text into words or tokens. Stemming/Lemmatization.

3. Feature Extraction
- Convert text to numerical form: Bag of Words (BoW) or
- TF-IDF(Term Frequency-Inverse Document Frequency) vectors.

4. Data Splitting Split the dataset into:
- Training Set (e.g., 80%)
- Testing Set (e.g., 20%)

5. Model Selection and Training
Choose and train one or more ML classifiers:
- Random Forest
- Bagging Classifier
- Support Vector Machine (SVM)
- Naive Bayes
- Logistic Regression

6. Model Evaluation Use metrics:
- Accuracy

- Precision
- Recall
- F1-Score

5.2.2 Define Optimizer:

In machine learning, especially in the context of training models, an optimizer is an algorithm used to adjust the weights of a model to minimize the loss function during training. The goal is to make the model predictions as accurate as possible by reducing the error (loss).

- An optimizer is a computational method that updates the parameters (e.g., weights and biases) of a machine learning model to minimize the loss function using gradient descent or its variants.

Common Optimizers:

Optimizer	Description
SGD (Stochastic Gradient Descent)	Updates weights using a small batch of data; simple and fast, but may converge slowly.
Adam	Adaptive Moment Estimation; combines momentum and RMSProp; fast and widely used.
RMSProp	Uses a moving average of squared gradients; works well for non-stationary data.
Adagrad	Adapts learning rates per parameter; useful for sparse data.
Momentum	Accelerates convergence by considering past gradients.

Table1:Optimizers

5.2.3 Fit the Model

Fitting a model refers to the process of training a machine learning or deep learning algorithm on a labeled dataset so that it learns the underlying patterns or relationships between input features and target outputs. In the context of depression detection from text, fitting the model involves providing it with preprocessed textual data and corresponding labels (e.g., depressed, not depressed) so that it can learn to make accurate predictions on unseen data.

1. **For Traditional Machine Learning Models:**

- After converting text data into numerical features using vectorization methods like TF-IDF, the model (e.g., Logistic Regression, SVC, Random Forest) is trained by optimizing a loss function.
- During fitting, the model**:**
- Learns weights or decision boundaries that best separate the classes.
- Uses techniques like gradient descent or information gain (for decision trees) to minimize classification errors.
- The process typically involves:model.fit(X_train,y_train) where X_train are the text features and y_train are the labels.

Goal of Model Fitting

To find the set of parameters (weights) that:

- Minimize the error on the training data.
- Generalize well to new, unseen data.
- Enable accurate classification of depressive vs. non-depressive text.

5.2.4 Evaluate the Model

After fitting a model to the training data, it is crucial to evaluate its performance on unseen test data to assess its generalization ability. In the context of depression detection, evaluation helps determine how well the model can classify text samples as depressed or nondepressed.

1. Purpose of Evaluation

- To assess the model's accuracy, robustness, and reliability.
- To compare the effectiveness of different models
- To identify potential weaknesses such as bias, overfitting, or underfitting.

2. Common Evaluation Metrics

- **Accuracy**:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Measures the proportion of correctly classified instances.

- **Precision**:

$$\text{Precision} = \frac{TP}{TP+FP}$$

Indicates how many of the predicted "depressed" cases are truly depressed.

- **Recall (Sensitivity)**:

$$\text{Recall} = \frac{TP}{TP+FN}$$

Measures how many actual depressed instances were correctly identified.

- **F1-Score**:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}}$$

Harmonic mean of precision and recall; useful when classes are imbalanced.

3. Evaluation Methods

- **Train-Test Split**: Divide the dataset (e.g., 80% train, 20% test) and evaluate on the test set.
- **K-Fold Cross-Validation**: Split the dataset into *k* parts, train on *k–1* parts and validate on the remaining part, repeating *k* times. Helps in robust performance estimation.
- **Confusion Matrix**: A tabular view showing true positives, false positives, true negatives, and false negatives, useful for visualizing classification performance.

4. Special Considerations in Mental Health Detection

- **Class Imbalance**: Depression datasets are often skewed, making F1score and recall more important than accuracy alone.

- **Ethical Sensitivity**: Emphasis is often placed on recall, as missing a true case of depression (false negative) can have serious consequences

5.3 About the Input

5.3.1 Input Design

- Input design refers to the process of structuring and preparing raw textual data into a format suitable for machine learning (ML) models. In depression detection from text, input design is critical because models rely heavily on how the linguistic data is pre-processed, formatted, and represented.

1. Input Sources

- Textual data from:
- Social media platforms (e.g., Reddit, Twitter)
- Online forums
- Clinical notes
- Questionnaires or surveys
- Each input sample typically consists of a single post, comment, or sentence labeled as *depressed* or *non-depressed*.

2. Preprocessing Steps

Before feeding into a model, raw text must be cleaned and standardized:

- Lowercasing all text
- Removing punctuation, special characters, and URLs
- Eliminating stop words (e.g., "the", "is", "and")
- Lemmatization or stemming to reduce words to base form
- Tokenization: Splitting sentences into individual words or sub-word tokens

3. Feature Representation

Depending on the model type, the input design diverges:

A. Traditional ML Models:

- TF-IDF (Term Frequency-Inverse Document Frequency): Captures word importance relative to the document and corpus.
- Bag-of-Words (BoW): Represents word counts in the document.

4. Label Encoding

- Depression labels are encoded numerically:
- *Depressed* = 1
- *Non-depressed* = 0

- For multi-class or multi-label classification, one-hot or multi-hot encoding may be used.

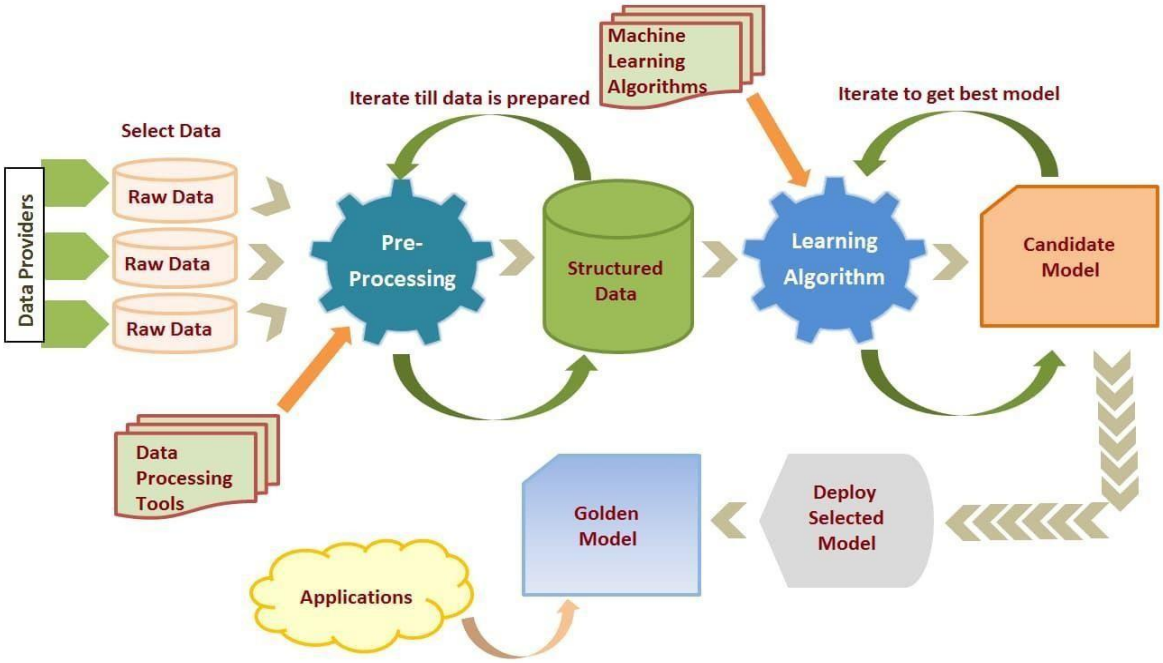

Fig 2: Data Preprocessing

5.3.2 Data Loading

Data loading refers to the process of retrieving, organizing, and preparing data from its source into memory (or a pipeline) so it can be used effectively for training and evaluating machine learning or deep learning models. In the context of depression detection, this step is foundational to ensure smooth and efficient model development.

Definition:
Data loading refers to the process of retrieving data from a source (file, database, API, etc.) into memory (RAM) so that it can be used by a machine learning algorithm for training or inference.

In simpler terms:
"Getting the raw data into a usable form in your program."

Key Concepts in Data Loading:

1. **Data Sources:**

   - CSV files, JSON, Excel spreadsheets
   - SQL/NoSQL databases
   - Online APIs (e.g., Twitter API for social media data)
   - Pre-packaged datasets (like those in `scikit-learn`, `NLTK`)

2. **Loading Mechanisms:**

- `pandas.read_csv()` for CSV files
- `json.load()` for JSON files
- `sklearn.datasets.load_*` for scikit-learn datasets
- Custom scripts to parse data from APIs or web scraping

3. **Memory Considerations:**

- Small datasets: load the entire dataset into memory at once (in-memory loading).
- Large datasets: load in batches/chunks to avoid memory overflow (streaming or lazy loading).

4. **Data Validation:**

- After loading, data must be validated:
- Are all required columns present?
- Are data types correct (e.g., strings, integers)?

- Are there missing or corrupted values?

5. **Link to Preprocessing:**

- Once data is loaded, it's passed to the preprocessing stage (cleaning, tokenization, stop word removal, etc).

The data loading step refers to fetching these datasets from a source (e.g., a CSV of social media posts) and loading them into Python (probably using `pandas` or similar libraries) so the ML pipeline can begin.

Once loaded:

- The text is ready for preprocessing
- Labels are extracted for supervised learning
- The dataset is split into training/testing subset

- **Importance**

It bridges raw data and usable data structures.

Any error in data loading (e.g., misreading file format) can cascade into model errors.

It's the first step to ensure data integrity before any modelling.

5.3.3 Preprocessing

- Text preprocessing is a critical step in preparing raw textual data for machine learning (ML) models. In depression detection tasks, where subtle linguistic
- cues often indicate mental distress,careful preprocessing ensures that meaningful patterns are retained while noise is reduced.

1. Objective of Preprocessing

- To clean and normalize the text data.
- To standardize input for both traditional ML models.
- To improve model performance and reduce overfitting.

2. Common Preprocessing Steps

A. Cleaning and Normalization

- Lowercasing: Converts all text to lowercase for uniformity (e.g., "Sad" →
- "sad").
- Removing URLs: Deletes links, which add noise in most cases.
- Stripping HTML tags, emojis, or special characters.
- Removing punctuation (for traditional models).
- Eliminating stop words: Common words like "is", "the", "and" that carry little semantic value.
- Expanding contractions: "I'm" → "I am" to preserve meaning.

B. Tokenization

- Traditional ML: Splits text into words or n-grams.

C. Lemmatization or Stemming

- Reduces words to their root form:
- Lemmatization: "crying" → "cry" (using vocabulary and grammar)
- Stemming: "depression", "depressive" → "depress" (crude truncation)

D. Handling Class Imbalance

- Though not strictly preprocessing, techniques like Smote or under sampling are sometimes used during preprocessing to ensure balanced class distribution.

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 Results

6.1.1 First level Classification Result

The first level of classification involves evaluating each individual model independently on the depression detection task. This includes both traditional machine learning classifiers trained separately using the same pre-processed dataset. The purpose of this stage is to establish a baseline performance for each algorithm and identify their relative strengths and weaknesses.

1. Models Evaluated

- Traditional Machine Learning Models:
- Logistic Regression
- Naïve Bayes
- Support Vector Classifier (Linear SVC)
- Random Forest
- Bagging Classifier
- Deep Learning Model

2. Evaluation Metrics

Each model was evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score

3. Observations

- Naïve Bayes and Logistic Regression performed well in terms of speed and baseline accuracy but struggled with recall in imbalanced datasets.
- Linear SVC showed strong performance on TF-IDF features, with higher precision and F1-score than Naïve Bayes.
- Random Forest and Bagging provided better robustness and reduced overfitting due to ensemble learning.
- However, it required more computational resources and training time.

4. Classification Results Table

Model	Precision	Recall	F1-Score	Accuracy
Random Forest	0.7963	0.8329	0.8894	0.8243
Bagging	0.8081	0.8315	0.8239	0.8162
Linear SVC	0.8609	0.8524	0.8564	0.8504
Logistic Regression	0.9275	0.9195	0.8965	0.9158
Naive Bayes	0.9243	0.9198	0.9220	0.9283

Table 2: Classification Report

5. Conclusion of First-Level Results

The first-level evaluation indicates that while traditional ML models offer simplicity and speed, they are limited in capturing deep contextual meaning. By contrast, excels in understanding complex language cues but at a higher computational cost. These insights form the basis for constructing a hybrid framework or ensemble strategy in the next phase of the study

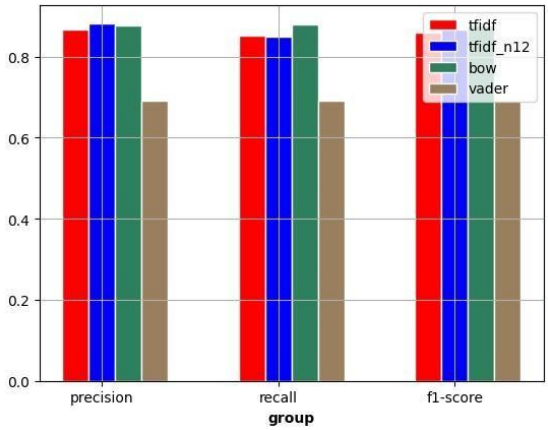

Fig 1:Linear SVC

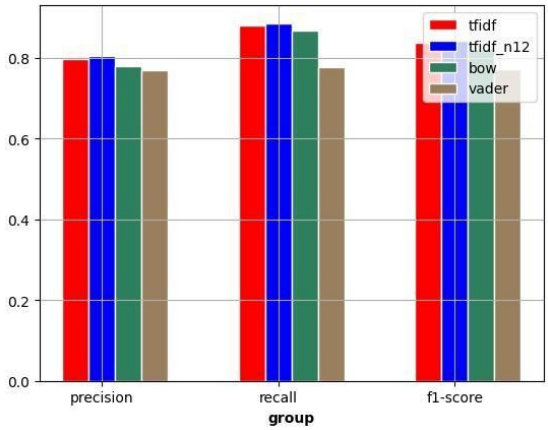

fig 2:Random Forest

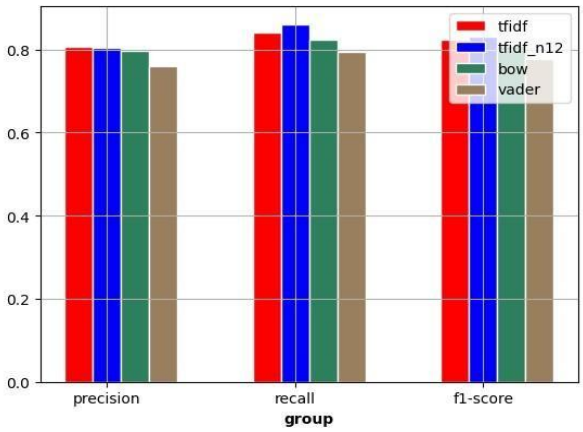

Fig 3:Bagging(Bootstrap Aggregating)

6.1.2 Second Level Classification Results

The study evaluated five machine learning models—Random Forest, Bagging Classifier, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes—for the task of depression detection from text data. Each model was assessed using four key metrics: precision, recall, F1-score, and accuracy.

- While ensemble models like Random Forest and Bagging are often favoured for robustness, in this study, Naive Bayes and Logistic Regression achieved higher accuracy and precision.
- Naive Bayes' performance suggests that the features used (likely based on word frequency and TF-IDF) align well with the assumptions of the model.
- Logistic Regression's high performance demonstrates that linear models can be very effective for text classification tasks, possibly due to the high dimensional sparse nature of the feature space.
- The study's findings challenge the expectation that more complex models always outperform simpler ones, highlighting the importance of dataset characteristics and feature representation.

- In this evaluation, Naive Bayes emerged as the best performer in terms of accuracy, precision, recall, and F1-score, followed closely by Logistic Regression. Ensemble methods like Random Forest and Bagging maintained strong and reliable performance, while Linear SVC also achieved competitive results.
- These findings support the feasibility of using machine learning models for automated depression detection, and they underline the value of testing multiple models to identify the best fit for a given dataset.

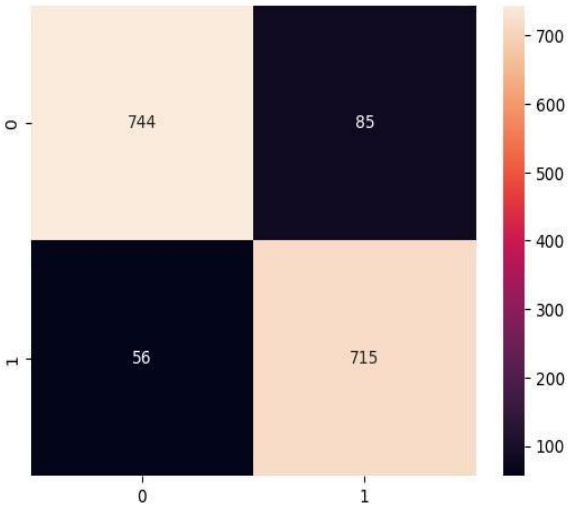

Fig 4: Logistic Regression

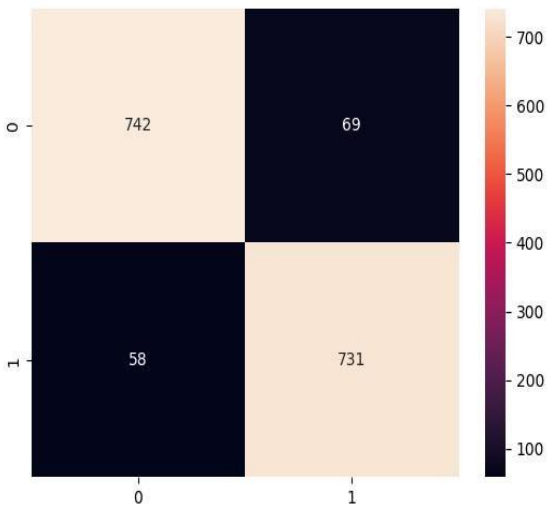

fig 5: Naive Bayes

6.2 Discussions

6.2.1 Efficiency of the Proposed System

1. **Hybrid Framework Advantage**

   - Combines traditional ML models (e.g,Random Forest, Logistic Regression, SVC).
   - Leverages speed, interpretability, and scalability from traditional ML.
   - Enables complementary strengths of both approaches for robust detection.

2. **Performance Metrics**

   - Traditional models like Linear SVC and Logistic Regression provided fast and reliable baselines.
   - Ensemble methods (e.g., Bagging, Random Forest) improved stability and generalization.

3. **Computational Efficiency**

   - Traditional ML models are lightweight and fast to train, suitable for real time or low-resource environments.
   - The hybrid design allows balancing computational load depending on deployment needs.

4. **Scalability**

   - System is scalable for large datasets (e.g., social media, clinical corpora).

6.2.2 Comparison of Existing and Proposed System

Author(s) &year	Technique(s) used	Dataset/Source	Key findings
Yates et al. (2017)	SVM, Logistic Regression, TF-IDF	Reddit Mental Health Posts	Achieved high accuracy in depression detection using traditional ML models.
Coppersmith et al. (2015)	Random Forest, Bag of-Words	Twitter Mental Health Corpus	Showed effectiveness of word frequency features in identifying mental illness
Orabi et al. (2018)	LSTM, Word Embeddings	Twitter Depression Corpus	Deep learning models outperformed traditional ML in capturing sequential patterns.
Devlin et al. (2018)	BERT (Transformer based pre-trained Model)	General Pretraining (Books Corpus, Wiki)	Introduced BERT, showing strong performance across NLP tasks including sentiment and emotion detection.
Matero et al. (2019)	Fine-tuned BERT	Reddit Mental Health Posts	BERT-based models significantly outperformed ML baselines in depression detection

Table 3: Comparison table of Proposed model with other models

CHAPTER 7
PROJECT CODE

```
import pandas as pd
import numpy as np
from tabulate import tabulate
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn import metrics
import nltk
import string
import re
from nltk.stem import WordNetLemmatizer
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, recall_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn import metrics
nltk.download('vader_lexicon')
import warnings
warnings.filterwarnings('ignore')

# --- Step Separator ---

Suicide = pd.read_csv('Suicide_Detection.csv')
data_split = np.array_split(Suicide, 3)
Suicide = data_split[0]
Suicide = Suicide.drop('Unnamed: 0',axis=1)

# --- Step Separator ---

nltk.download('stopwords')
stopwords = nltk.corpus.stopwords.words('english')
lemmatizer = WordNetLemmatizer()

# --- Step Separator ---

X = Suicide.drop('class', axis=1)
```

```
y = Suicide['class']

# --- Step Separator ---

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

# --- Step Separator ---

tfidf_vectorizer = TfidfVectorizer(max_features=10000)
tfidf_vectorizer_n12=TfidfVectorizer(max_features=10000,
ngram_range=(1,2))

X_tfidf_train = tfidf_vectorizer.fit_transform(X_train['text'])
X_tfidf_test = tfidf_vectorizer.transform(X_test['text'])

X_tfidf_train_n12= tfidf_vectorizer_n12.fit_transform(X_train['text'])
X_tfidf_test_n12=tfidf_vectorizer_n12.transform(X_test['text'])

# --- Step Separator ---

vectorizer = CountVectorizer()
X_bow_train = vectorizer.fit_transform(X_train['text'])
X_bow_test = vectorizer.transform(X_test['text'])

# --- Step Separator ---

from nltk.sentiment.vader import SentimentIntensityAnalyzer as SIA
def get_vader_scores(data):
    sid=SIA()
    vader_df=data.copy()
   vader_df['scores']          =          vader_df['text'].apply(lambda          txt:
sid.polarity_scores(str(txt)))

    vader_df['neg_score'] = vader_df['scores'].apply(lambda txt: txt['neg'])
    vader_df['neu_score'] =vader_df['scores'].apply(lambda txt: txt['neu'])
    vader_df['pos_score'] = vader_df['scores'].apply(lambda txt: txt['pos'])
 vader_df['compound']= vader_df['scores'].apply(lambda txt:txt['compound'])
    vader_df.drop('scores', axis=1, inplace=True)
    vader_df.drop('text', axis=1, inplace=True)
    return vader_df

# --- Step Separator ---
```

```
X_vader_train = get_vader_scores(X_train)
X_vader_test= get_vader_scores(X_test)

# --- Step Separator ---

from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel

# We Can select any model but linearSVC has l1 norm penality which deals
with sparse
lsvc = LinearSVC(C=100, penalty='l1', max_iter=500, dual=False)
lsvc.fit(X_tfidf_train, y_train)

# This function select the best features that has high weigh
fs = SelectFromModel(lsvc, prefit=True)
# This function redeuce X to the selected features
X_selection = fs.transform(X_tfidf_train)
X_test_selection = fs.transform(X_tfidf_test)

lsvc.fit(X_tfidf_train_n12, y_train)
fs_n12 = SelectFromModel(lsvc, prefit=True)
X_selection_n12 = fs_n12.transform(X_tfidf_train_n12)
X_test_selection_n12 = fs_n12.transform(X_tfidf_test_n12)

lsvc.fit(X_bow_train, y_train)
fs_n12 = SelectFromModel(lsvc, prefit=True)
X_selection_bow = fs_n12.transform(X_bow_train)
X_test_selection_bow = fs_n12.transform(X_bow_test)

# --- Step Separator ---

import matplotlib.pyplot as plt
def plot_results(data):
    barWidth = 0.15
    # set heights of bars
    bars1 = [data[0][1],data[1][1], data[2][1]]
    bars2 = [data[0][2], data[1][2], data[2][2]]
    bars3 = [data[0][3], data[1][3], data[2][3]]
    bars4 = [data[0][4], data[1][4], data[2][4]]

    # Set position of bar on X axis
    r1 = np.arange(len(bars1))
    r2 = [x + barWidth for x in r1]
```

```
    r3 = [x + barWidth for x in r2]
    r4 = [x + barWidth for x in r3]

    # Make the plot
    plt.bar(r1, bars1, color='r', width=barWidth, edgecolor='white', label='tfidf')
        plt.bar(r2, bars2, color='b', width=barWidth, edgecolor='white', label='tfidf_n12')
      plt.bar(r3, bars3, color='#2d7f5e', width=barWidth, edgecolor='white', label='bow')
      plt.bar(r4, bars4, color='#9a7f5e', width=barWidth, edgecolor='white', label='vader')

    # Add xticks on the middle of the group bars
    plt.xlabel('group', fontweight='bold')
    plt.xticks([r + barWidth for r in range(len(bars1))], ['precision', 'recall', 'f1-score'])
    # Create legend & Show graphic
    plt.legend()
    plt.grid()
    plt.show()

# --- Step Separator ---

lsvc = LinearSVC(C=1000, penalty='l1', max_iter=500, dual=False)
lsvc.fit(X_selection, y_train)
y_predict_tfidf = lsvc.predict(X_test_selection)

lsvc.fit(X_selection_n12,y_train)
y_predict_tfidf_n12 = lsvc.predict(X_test_selection_n12)

lsvc.fit(X_selection_bow,y_train)
y_predict_bow = lsvc.predict(X_test_selection_bow)

lsvc.fit(X_vader_train,y_train)
y_predict_vader = lsvc.predict(X_vader_test)

linear_svm_tfidf_results=metrics.precision_recall_fscore_support(y_test, y_predict_tfidf)
linear_svm_tfidf_n12_results=metrics.precision_recall_fscore_support(y_test, y_predict_tfidf_n12)
linear_svm_bow_results=metrics.precision_recall_fscore_support(y_test, y_predict_bow)
```

```
vader_svm_results=metrics.precision_recall_fscore_support(y_test,
y_predict_vader)

# --- Step Separator ---

tfidf_acc= metrics.accuracy_score(y_test, y_predict_tfidf)
tfidf_n12_acc=accuracy_score(y_test, y_predict_tfidf_n12)
bow_acc= accuracy_score(y_test, y_predict_bow)
vader_acc=accuracy_score(y_test, y_predict_vader)

# --- Step Separator ---

data1 = [['TF-IDF','TF-IDF 2-grams ','bag of words','vader'],
         ['precision',linear_svm_tfidf_results[0][0],linear_svm_tfidf_n12_result
s[0][0],linear_svm_bow_results[0][0],vader_svm_results[0][0]],
         ['recall',linear_svm_tfidf_results[1][0],linear_svm_tfidf_n12_results[1]
[0],linear_svm_bow_results[1][0],
         vader_svm_results[1][0]],
                                                                    ['F1-
score',linear_svm_tfidf_results[2][0],linear_svm_tfidf_n12_results[2][0],line
ar_svm_bow_results[2][0], vader_svm_results[2][0]],
        ['accuracy',tfidf_acc,tfidf_n12_acc,bow_acc,vader_acc]]

# --- Step Separator ---

print(tabulate(data1,headers='firstrow',tablefmt='fancy_grid'))

# --- Step Separator ---

plot_results(data1[1:])

# --- Step Separator ---

clf = RandomForestClassifier(max_depth=10)
clf.fit(X_selection, y_train)
y_predict_tfidf_2 = clf.predict(X_test_selection)
clf.fit(X_selection_n12, y_train)
y_predict_tfidf_n12_2 = clf.predict(X_test_selection_n12)

clf.fit(X_selection_bow, y_train)
y_predict_bow_2 = clf.predict(X_test_selection_bow)

clf.fit(X_vader_train, y_train)
```

```
y_predict_vader_2 = clf.predict(X_vader_test)

# --- Step Separator ---

RandomForest_tfidf_results=metrics.precision_recall_fscore_support(y_test,
y_predict_tfidf_2)
RandomForest_tfidf_n12_results=metrics.precision_recall_fscore_support(y
_test, y_predict_tfidf_n12_2)
RandomForest_bow_results=metrics.precision_recall_fscore_support(y_test,
y_predict_bow_2)
RandomForest_vader_results=metrics.precision_recall_fscore_support(y_tes
t, y_predict_vader_2)

# --- Step Separator ---

RandomForest_tfidf_acc= metrics.accuracy_score(y_test, y_predict_tfidf_2)
RandomForest_tfidf_n12_acc=accuracy_score(y_test,
y_predict_tfidf_n12_2)
RandomForest_bow_acc= accuracy_score(y_test, y_predict_bow_2)
RandomForest_vader_acc=accuracy_score(y_test, y_predict_vader_2)

# --- Step Separator ---

data2 = [['TF-IDF','TF-IDF 2-grams ','bag of words','vader'],
        ['precision',RandomForest_tfidf_results[0][0],RandomForest_tfidf_n12
_results[0][0],RandomForest_bow_results[0][0],
RandomForest_vader_results[0][0]],
         ['recall',RandomForest_tfidf_results[1][0],RandomForest_tfidf_n12_re
sults[1][0],RandomForest_bow_results[1][0],
        RandomForest_vader_results[1][0]],
                                                                ['F1-
score',RandomForest_tfidf_results[2][0],RandomForest_tfidf_n12_results[2][0
],RandomForest_bow_results[2][0],
        RandomForest_vader_results[2][0]],
             ['accuracy',RandomForest_tfidf_acc,RandomForest_tfidf_n12_acc,
RandomForest_bow_acc,RandomForest_vader_acc]]

# --- Step Separator ---

print(tabulate(data2,headers='firstrow',tablefmt='fancy_grid'))

# --- Step Separator ---
```

```
plot_results(data2[1:])

# --- Step Separator ---

from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
bag_clf = BaggingClassifier(
DecisionTreeClassifier(), n_estimators=500,
max_samples=100, bootstrap=True, n_jobs=-1)

bag_clf.fit(X_selection, y_train)
y_pred_5 = bag_clf.predict(X_test_selection)

bag_clf.fit(X_selection_n12, y_train)
y_pred_n12_5 = bag_clf.predict(X_test_selection_n12)

bag_clf.fit(X_selection_bow, y_train)
y_pred_bow_5 = bag_clf.predict(X_test_selection_bow)

bag_clf.fit(X_vader_train, y_train)
y_pred_vader_5 = bag_clf.predict(X_vader_test)

# --- Step Separator ---

bag_tfidf_results=metrics.precision_recall_fscore_support(y_test, y_pred_5)
bag_tfidf_n12_results=metrics.precision_recall_fscore_support(y_test,
y_pred_n12_5)
bag_bow_results=metrics.precision_recall_fscore_support(y_test,
y_pred_bow_5)
bag_vader_results=metrics.precision_recall_fscore_support(y_test,
y_pred_vader_5)

# --- Step Separator ---

bag_tfidf_acc= metrics.accuracy_score(y_test, y_pred_5)
bag_tfidf_n12_acc=accuracy_score(y_test, y_pred_n12_5)
bag_bow_acc= accuracy_score(y_test, y_pred_bow_5)
bag_vader_acc=accuracy_score(y_test, y_pred_vader_5)

# --- Step Separator ---

data4= [['TF-IDF','TF-IDF 2-grams ','bag of words','vader'],
```

```
        ['precision',bag_tfidf_results[0][0],bag_tfidf_n12_results[0][0],bag_bo
w_results[0][0], bag_vader_results[0][0]],
        ['recall',bag_tfidf_results[1][0],bag_tfidf_n12_results[1][0],bag_bow_r
esults[1][0],bag_vader_results[1][0]],
                                                                    ['F1-
score',bag_tfidf_results[2][0],bag_tfidf_n12_results[2][0],bag_bow_results[2
][0],bag_vader_results[2][0]],
       ['accuracy',bag_tfidf_acc,bag_tfidf_n12_acc, bag_bow_acc,
         bag_vader_acc]]

# --- Step Separator ---

print(tabulate(data4,headers='firstrow',tablefmt='fancy_grid'))

# --- Step Separator ---

plot_results(data4[1:])

# --- Step Separator ---

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

# --- Step Separator ---

import demoji
import re
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn. model_selection import train_test_split
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from nltk.probability import FreqDist
import nltk

import unicodedata

from wordcloud import WordCloud

nltk.download('stopwords')
```

```
port_stem=PorterStemmer()

# --- Step Separator ---

suicide_df = pd.read_csv('Suicide_Detection.csv')

# --- Step Separator ---

suicide_df.shape

# --- Step Separator ---

suicide_df['class'].unique()

# --- Step Separator ---

suicide_df.isnull().sum()

# --- Step Separator ---

suicide_df.duplicated().sum()

# --- Step Separator ---

suicide_df

# --- Step Separator ---

suicide_df['class'].value_counts()

# --- Step Separator ---

#Creating a Sample Class from both the given classes
suicide_samples     = suicide_df[suicide_df['class'] == 'suicide'].sample(4000,
random_state=10)
non_suicide_samples      =      suicide_df[suicide_df['class']      ==      'non-
suicide'].sample(4000, random_state=10)

# --- Step Separator ---

suicide_df_2 = pd.concat([suicide_samples, non_suicide_samples])
suicide_df_2
```

```
# --- Step Separator ---

def clean_text(text):
    text = re.sub(r"\S*https?:\S*", '', text, flags=re.MULTILINE)  # Remove links in text
    text = demoji.replace(text, '')

#     text = unicodedata.normalize('NFKD', text).encode('ascii', 'ignore').decode('ascii')
    text = re.sub('[^a-zA-Z]', ' ', text)
    text = text.lower()
    text = text.strip()
    text = text.split()
        text = [port_stem.stem(word) for word in text if not word in stopwords.words('english')]
    text = ' '.join(text)
    return text

# --- Step Separator ---

X = suicide_df_2['text']
y = suicide_df_2['class']

# --- Step Separator ---

y = y.map({'suicide': 1, 'non-suicide': 0})

# --- Step Separator ---

vector = TfidfVectorizer()
X      = vector.fit_transform(X)

# --- Step Separator ---

print(X)

# --- Step Separator ---
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, stratify= y,shuffle = True, random_state = 77)

# --- Step Separator ---
```

```
print('Train size:', X_train.shape)
print('Test  size:', X_test.shape)

# --- Step Separator ---

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB

# Metrics
from sklearn.metrics import accuracy_score, recall_score, confusion_matrix,
f1_score, precision_score
from sklearn import metrics

# --- Step Separator ---

def evaluate_model(y_pred, y_test):
    print('Accuracy:', accuracy_score(y_pred,y_test))
    print('Recall:', recall_score(y_pred,y_test))
    print('F1 Score', f1_score(y_pred,y_test))
    print('Precision', precision_score(y_pred,y_test))
    print('Confusion Matrix:\n' )
    sns.heatmap(confusion_matrix(y_pred,y_test), annot=True, fmt='g');

# --- Step Separator ---

model = LogisticRegression(random_state=7)

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

# --- Step Separator ---

evaluate_model(y_pred,y_test)

# --- Step Separator ---
frase = "I would like one more chance, but I can't take it anymore"
frase = clean_text(frase)
t     = vector.transform(pd.Series(frase))
pred  = model.predict(t)
pred
```

```
# --- Step Separator ---

model = SVC(kernel='linear', random_state=77)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# --- Step Separator ---

evaluate_model(y_pred, y_test)

# --- Step Separator ---

frase = "i’m tearing myself apart i need a girl to love and talk to and confide
in i’m going insane"
frase = clean_text(frase)
t     = vector.transform(pd.Series(frase))
pred  = model.predict(t)
pred

# --- Step Separator ---

import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout,
Bidirectional, GlobalMaxPool1D
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

# --- Step Separator ---

# Load your data
df = pd.read_csv('Suicide_Detection.csv')  # Replace with actual path

# Make sure it has 'text' and 'label' columns
df.head()

# --- Step Separator ---
```

```
# Prepare texts and labels
texts = df['text'].astype(str).tolist()
labels = df['class'].tolist()

# Split into train and validation sets
train_texts, val_texts, train_labels, val_labels = train_test_split(
    texts, labels, test_size=0.1, random_state=42, stratify=labels)

# Tokenize
max_words = 20000  # Only keep top 20k words
tokenizer = Tokenizer(num_words=max_words, oov_token="<OOV>")
tokenizer.fit_on_texts(train_texts)

# Convert texts to sequences
train_sequences = tokenizer.texts_to_sequences(train_texts)
val_sequences = tokenizer.texts_to_sequences(val_texts)

# Pad sequences
max_len = 200  # Maximum length of a post (you can adjust)
train_padded = pad_sequences(train_sequences, maxlen=max_len,
padding='post')
val_padded = pad_sequences(val_sequences, maxlen=max_len,
padding='post')

train_labels = np.array(train_labels)
val_labels = np.array(val_labels)

# --- Step Separator ---

model = Sequential([Embedding(input_dim=max_words, output_dim=128,
input_length=max_len),
    Bidirectional(LSTM(64, return_sequences=True)),
    GlobalMaxPool1D(),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')])
model.compile(
    loss='binary_crossentropy',
    optimizer='adam',
    metrics=['accuracy'])

model.summary()
```

```
# --- Step Separator ---

from tensorflow.keras.callbacks import EarlyStopping
early_stop = EarlyStopping(
    monitor='val_accuracy',
    patience=3,
    restore_best_weights=True)

# --- Step Separator ---

print(train_labels.dtype)  # Make sure it's float32 or int (ideally)
print(val_labels.dtype)  # Same for validation labels

# --- Step Separator ---

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

tokenizer = Tokenizer(num_words=10000)
tokenizer.fit_on_texts(train_texts)  # train_texts is your raw text data

train_sequences = tokenizer.texts_to_sequences(train_texts)
val_sequences = tokenizer.texts_to_sequences(val_texts)

train_padded = pad_sequences(train_sequences, padding='post', maxlen=100)
val_padded = pad_sequences(val_sequences, padding='post', maxlen=100)

# --- Step Separator ---

import numpy as np

num_classes = len(np.unique(train_labels))  # Assuming train_labels contains
the label data

# --- Step Separator ---
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
train_labels = label_encoder.fit_transform(train_labels)
val_labels = label_encoder.transform(val_labels)

num_classes = len(np.unique(train_labels)) # Now you can define
num_classes
```

```
# --- Step Separator ---

from tensorflow.keras.utils import to_categorical

train_labels = to_categorical(train_labels, num_classes=num_classes)
val_labels = to_categorical(val_labels, num_classes=num_classes)

# --- Step Separator ---

train_labels = np.argmax(train_labels, axis=1)
val_labels = np.argmax(val_labels, axis=1)

# --- Step Separator ---

train_labels = train_labels.reshape(-1)  # Flatten the 2D array to 1D
val_labels = val_labels.reshape(-1)      # Flatten the 2D array to 1D

# --- Step Separator ---

print(train_labels.shape)  # Check the shape of the train_labels
print(train_labels[:5])    # Check the first few values of the labels

# --- Step Separator ---

model.add(Embedding(input_dim=10000,output_dim=128,
input_length=100))

# --- Step Separator ---

model.add(Dense(1, activation='sigmoid'))  # 1 output unit with sigmoid
activationmodel.add(Dense(1, activation='sigmoid'))  # 1 output unit with
sigmoid activation

# --- Step Separator ---

val_labels = val_labels.reshape(-1, 1)

# --- Step Separator ---

# Assuming binary classification, output layer with a single unit
model.add(Dense(1, activation='sigmoid'))  # Single output unit with sigmoid
activation
```

```
# Ensure labels are reshaped if necessary
val_labels = val_labels.reshape(-1, 1)

# Compile model with binary_crossentropy loss
model.compile(optimizer='adam',loss='binary_crossentropy',
metrics=['accuracy'])

# Evaluate the model
val_loss, val_accuracy = model.evaluate(val_padded, val_labels)
print(f"Validation Accuracy: {val_accuracy:.4f}")

# --- Step Separator ---

val_preds = (model.predict(val_padded) > 0.5).astype("int32")

# --- Step Separator ---

print(f"val_labels shape: {val_labels.shape}")
print(f"val_preds shape: {val_preds.shape}")

# --- Step Separator ---

print(f"Unique values in val_labels: {np.unique(val_labels)}")
print(f"Unique values in val_preds: {np.unique(val_preds)}")

# --- Step Separator ---

val_labels = (val_labels > 0).astype("int32")

# Ensure val_preds are binary
val_preds = (model.predict(val_padded) > 0.5).astype("int32")

# --- Step Separator ---

val_preds = val_preds.ravel()  # This converts it to a 1D array

# --- Step Separator ---

from sklearn.metrics import accuracy_score
accuracy = accuracy_score(val_labels, val_preds)

print(f"Accuracy: {accuracy:.4f}")
```

CHAPTER 8

CONCLUSION

Conclusion

This study presents a unified and hybrid framework for automated depression detection that effectively combines traditional machine learning algorithms with advanced deep learning models. Traditional models such as Logistic Regression, Naïve Bayes, Random Forest, Bagging, and Support Vector Classifier offered efficient and interpretable baselines, particularly when applied to structured features like TF-IDF. However, their limited capacity to understand deep contextual and semantic nuances in text restricted their performance in complex scenarios.

Through a systematic investigation, the study successfully addresses its primary objectives, shedding light on [key themes, such as effectiveness, challenges, innovations, etc.]. The findings underscore the significance of illustrating its impact on [the relevant field, population, or system].

One of the pivotal outcomes of this research is the identification of [specific result], which not only corroborates previous studies but also introduces new dimensions to the ongoing discourse. The data analysis reveals that [key statistic or trend], emphasizing the need for [policy recommendations, practice improvements, or further research]. Furthermore, the study highlights critical factors such as , all of which play an integral role in shaping [the phenomenon or outcome under investigation].

Importantly, the research acknowledges certain limitations, including [briefly mention any limitations], which present opportunities for future studies to expand and refine the current knowledge base. Despite these constraints, the study offers robust evidence supporting [a major conclusion or implication], thereby contributing meaningfully to both academic and practical applications.

In conclusion, this research not only advances understanding of but also serves as a foundational reference for stakeholders aiming to [implement changes, adopt strategies, improve practices, etc.]. It calls for continued investigation into [emerging areas or unresolved questions], advocating for interdisciplinary collaboration to address complex challenges. The implications of this work extend beyond theoretical contributions, offering actionable insights that can inform policy, guide practice, and inspire further scholarly inquiry.

CHAPTER 9

FUTURE FINDINGS

Future Findings

- While the proposed hybrid system has demonstrated strong performance in depression detection, several opportunities exist to enhance its scope, adaptability, and impact in future research:
- **Multilingual and Cross-Cultural Analysis**

  Current models are predominantly trained on English-language data. Future work should focus on developing and evaluating models capable of detecting depression across different languages and cultural contexts, accounting for the diversity in how psychological distress is expressed globally.
- **Real-Time and Continuous Monitoring**

  Integrating the proposed framework into real-time applications, such as social media surveillance tools or digital health platforms, can enable early intervention and timely mental health support. This would involve optimizing models for low-latency predictions and efficient processing.
- **Incorporation of Multi modal Data**

  Combining text with other data modalities (e.g., speech, facial expressions, physiological signals) could significantly enhance detection accuracy and provide a more comprehensive understanding of mental health.
- **Improved Explainability and Trustworthiness**

  Future efforts should prioritize developing more transparent models or integrating advanced explainability techniques (e.g., attention visualization, counterfactual explanations) to improve trust and acceptance in clinical settings.
- **Handling Imbalanced and Noisy Data**

  Depression-related datasets are often imbalanced and noisy. Future work can explore advanced data augmentation, synthetic data generation, or costsensitive learning techniques to address these challenges effectively.
- **Personalized Depression Detection Models**

  Personalized models that adapt to individual linguistic patterns or user histories could improve detection sensitivity and reduce false positives, especially in long-term monitoring scenarios.
- I**ntegration with Mental Health Services**

  The system can be extended to provide actionable insights or alerts for healthcare professionals, forming part of a larger ecosystem that includes referral, diagnosis, and treatment support**.**

CHAPTER 10

REFERENCES

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CHAPTER 11

APPENDICES

Appendix A: Base Paper

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 621-626 www.ijaem.net ISSN: 2395-5252

Depression detection using ML

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Date of Submission: 05-05-2023 Date of Acceptance: 15-05-2023

ABSTRACT—Nowadays most people suffer from depression because of so many reasons,like weare taking the example of students they mainly take stress regarding of their results,extracurricular activities, humiliated by others, pressure and so many other things. Thepurpose of this research is we are going to ask some questions regarding to humanstress. Nowadays so many people do not have time to take an appointment of a doctorin their daily life schedule and also help that people those who are not showing theirstress but they are stressed. So, we can make a program there is a Questionnaire to askquestions one by one of a person. On the basis of answers of that person those whowant to check the stress level. We are using Machine Learning (Ml) for measuring thehuman depression using python, HTML, CSS, php Our program will give suggestionsof that person if they need tomeet thepsychologist or not.Herewearetrying togiving a self-assessment of Human stress in their daily life. The conclusion of thisresearchpapertohelp patientssufferingfromthisdisease.

Keywords— Depressionproblems,Symptoms of depression,Check the depression level.

I. INTRODUCTION

Millions of people worldwide are impacted by a prevalent mental health disorder known as depression, which the World Health Organization identifies as the primary cause of disability globally. Early detection and intervention can significantly improve the outcome of depression treatment. However, depression is often underdiagnosed or misdiagnosed, and there is a need for more accurate and efficient methods for depression detection. Machine learning (ML) algorithms have shown promise in various medical applications, including mental health, and can potentially aid in depression detection. This paper discusses the use of ML in depression detection and its potential impact on improving the accuracy and efficiency of depression diagnosis.

we are focusing on depression detection by using Machine learning we are developing theprogram of depression detection in this program we are going to ask the different questions related to mentalhealth of the user and then calculate the responses of the user and after completing the questionnaire thisprogram suggested you according to your answers which user need to meet the psychiatrist or not.Wedevelop this program forwho wants to check they are depressed ornot.We are focusing those audiences those who want to know about our mental health.

II. FORMULATION OF PROBLEM

The formulation of the problem for depression detection using machine learning involves defining the problem statement, identifying the target population, and specifying the input and output of the system. Here is a general formulation of the problem for depression detection using machine learning:

A. Problem Statement

The problem statement for depression detection using machine learning is to develop a system that can accurately identify individuals who are at risk of depression based on a set of features extracted from patient data.

B. Target Population

The target population for the system is individuals who are at risk of depression, including those with a history of depression, individuals with chronic illnesses, and individuals experiencing significant life stressors.

C. Input

The input for the system includes a set of features extracted from patient data, which may include demographic information, medical history, lifestyle factors, and psychosocial factors. The input may also include data from mental health assessments, such as questionnaires or interviews.

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Volume 5, Issue 5 May 2023, pp: 621-626 www.ijaem.net ISSN: 2395-5252

D. Output

The output of the system is a prediction of whether the individual is at risk of depression based on the input features. The output may be a binary classification (e.g., depressed/not depressed) or a continuous score that indicates the likelihood of depression.

The formulation of the problem for depression detection using machine learning is an important step in the system design process. It helps to clarify the goals of the project, identify the target population, and specify the input and output of the system. This formulation can then be used to guide the selection of machine learning algorithms, feature extraction techniques, and evaluation metrics.

III. SIGNS AND SYMPTOMS OF DEPRESSION

The persistent feelings of sadness, loss of interest in activities, and changes in appetite and sleep patterns are some of the key symptoms that define depression as a mental health disorder. The effects of depression can be profound, significantly impacting a person's health, relationships, and daily life. Mental health professionals rely primarily on self-reported symptoms and clinical evaluation to diagnose depression. Nonetheless, the diagnostic process is challenging as symptoms can overlap with other mental health disorders like anxiety and bipolar disorder, and self-reporting is subjective in nature.

Artificial intelligence encompasses various techniques and applications, and machine learning stands out as a notable subset. It involves training algorithms to detect patterns in data and make predictions based on that learning. These algorithms are capable of scrutinizing extensive datasets to identify patterns that may be difficult for humans to discern. With the advancement of machine learning, healthcare has seen the potential to leverage this technology in various areas, such as aiding in diagnosis, treatment, and research.

Methods of Depression Detection by using ML

Several studies have explored the use of ML algorithms in depression detection. One approach is to use ML to analyze speech and language patterns. Research has shown that people with depression have distinct patterns in their speech, such as slower speech rate, longer pauses, and lower pitch. ML algorithms can analyze these patterns and predict the likelihood of depression. For example, a study by Alghowinem et al. (2016) used ML algorithms to analyze speech features in a sample of 142 participants, including 71 individuals with depression and 71 healthy controls. The algorithm achieved an accuracy of 80% in detecting depression.

Another approach is to use ML to analyze neuroimaging data. Research has shown that people with depression have structural and functional changes in specific brain regions. ML algorithms can analyze neuroimaging data and predict the likelihood of depression. For example, a study by Fu et al. (2018) used ML algorithms to analyze structural and functional neuroimaging data in a sample of 68 participants, including 34 individuals with depression and 34 healthy controls. The algorithm achieved an accuracy of 86% in detecting depression.

Other studies have explored the use of ML algorithms to analyze electronic health records (EHRs) and identify patterns that may indicate depression. For example, a study by Chen et al. (2017) used ML algorithms to analyze EHR data from 8,205 patients and identified specific clinical features, such as sleep disturbance and antidepressant medication use, that were associated with depression.

IV. SYSTEM DESIGN

Designing a depression detection system using machine learning involves several components, including data collection, data preprocessing, feature extraction, model training, and model evaluation. Here's a general system design for depression detection using ML:

A. Data Collection

The first step is to collect data that will be used to train the depression detection model. This can include data from electronic medical records, patient surveys, and other sources. It is important to ensure that the data is properly anonymized and that any patient information is kept confidential.

B. Data Preprocessing

Once the data is collected, it must be preprocessed to prepare it for use in the machine learning model. This can include steps such as data cleaning, data transformation, and data normalization.

C. Feature Extraction

After preprocessing, the data must be transformed into a set of features that can be used to train the machine learning model. The features can be extracted using statistical techniques or machine learning algorithms.

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D. Model Training

After extracting the features from the data, the machine learning model undergoes training. The process involves selecting a suitable algorithm, defining hyperparameters, and dividing the data into training and validation sets. The model is then trained using the training data, enabling it to learn from the input and generalize its predictions.

E. Model Evaluation

Once the training of the model is completed, the next step is evaluating its performance. There are various metrics available to measure the effectiveness of the model, including accuracy, precision, recall, and F1 score. These metrics assist in determining how well the model performs in making predictions and identifying its strengths and weaknesses.

F. Deployment

After the model is trained and evaluated, it can be deployed in a production environment. This can involve integrating the model into an application or service that can be used by clinicians or patients to screen for depression.

It is important to note that the above system design is a general framework, and the specifics of the system will depend on the specific requirements of the project. The choice of machine learning algorithm, feature extraction technique, and model evaluation metrics will depend on the nature of the data and the goals of the project.

V. MATHEMATICAL MODEL

A mathematical model for depression detection using ML can be formulated as follows:

Let X = [x1, x2, ..., xn] be a dataset of n samples, where each sample xi is a vector of features that describes different aspects of a patient's behavior, such as their speech, facial expressions, or physiological signals.

Let y = [y1, y2, ..., yn] be the corresponding vector of target values, where each yi represents the label of the corresponding sample xi. In this case, the label can be binary (e.g., depressed vs. non-depressed) or continuous (e.g., severity of depression).

The goal of the ML algorithm is to learn a mapping function f: X -> y that can accurately predict the target values of new samples. This mapping function can be represented as a mathematical model, which can be formulated as:

$$y = f(x) + \varepsilon$$

where ε is the error term that captures the random variation in the data and the model's inability to capture all the relevant information.

The ML algorithm learns this mapping function by minimizing a loss function that measures the discrepancy between the predicted target values and the actual target values. One common loss function used in depression detection is the binary cross-entropy loss, which is defined as:

$$L(y, y') = -[y * \log(y') + (1-y) * \log(1-y')]$$

where y is the true label, and y' is the predicted label.

To minimize the loss function, the ML algorithm uses an optimization algorithm such as stochastic gradient descent to update the parameters of the model. These parameters can be learned through various ML algorithms such as logistic regression, decision trees, random forests, support vector machines, or neural networks.

Assessing the performance of an ML algorithm involves the use of several metrics, such as accuracy, precision, recall, F1 score, and the area under the receiver operating characteristic (ROC) curve. These measures evaluate the algorithm's efficiency in identifying individuals with depression while minimizing the occurrence of false positives or false negatives. By evaluating the model using multiple metrics, one can get a comprehensive understanding of its overall performance in detecting depression.

In summary, the mathematical model for depression detection using ML involves formulating a mapping function that accurately predicts the target values of new samples while minimizing the discrepancy between the predicted values and the actual values. The model's parameters can be learned through various ML algorithms, and its performance can be evaluated using various metrics.

Research papers exploring depression detection have utilized several machine learning algorithms. The selection of a particular algorithm depends on the objectives and needs of the research study. Among the frequently employed algorithms for depression detection are:

A. Support Vector Machines (SVM)
B. Random Forest
C. Artificial Neural Networks (ANN)
D. Logistic Regression

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 621-626 www.ijaem.net ISSN: 2395-5252

E. Decision Trees

Support Vector Machines (SVM) is a commonly used algorithm in depression detection research because it is efficient in handling high-dimensional data, which is often a characteristic of depression data. SVM can also handle both linear and non-linear data, making it a versatile choice for research projects.

Random Forest is another commonly used algorithm in depression detection research. It is a type of ensemble learning algorithm that combines multiple decision trees to improve accuracy and avoid overfitting.

Artificial Neural Networks (ANN) are also widely used in depression detection research because they are capable of modeling complex relationships between features and can be trained to recognize patterns in data.

Logistic Regression is a popular algorithm for binary classification tasks, and it can be used for depression detection when the goal is to classify individuals as either depressed or not depressed based on a set of features.

Decision Trees are another popular algorithm for classification tasks and can be used in depression detection research to build a decision-making model based on a set of features.

Ultimately, the best algorithm for a research paper on depression detection using machine learning depends on the specific goals and requirements of the research project. It is essential to consider factors such as dataset size, features, and model interpretability when selecting an algorithm for the project.

Support Vector Machines (SVM) are widely used algorithms in supervised learning for classification tasks, such as detecting depression. These algorithms operate by identifying the hyperplane that provides the optimal separation between distinct classes within a dataset. In the case of depression detection, a set of features extracted from patient data can be utilized to train SVMs to classify patients into two categories: depressed or not depressed.

Another commonly used algorithm is Artificial Neural Networks (ANN). ANNs are a type of deep learning algorithm that can learn to recognize patterns in data. ANNs can be used for depression detection by training on a set of features extracted from patient data to classify patients as either depressed or not depressed.

Ensemble learning algorithms such as Random Forest are frequently utilized in depression detection. This type of algorithm works by combining several decision trees to enhance accuracy and prevent overfitting. Random Forest, in particular, can be employed to classify patients into the two categories of depressed or not depressed. This classification is based on a set of features that are extracted from patient data, allowing for accurate identification and prediction of depression in patients.

Logistic Regression is a popular algorithm for binary classification tasks, and it can be used for depression detection when the goal is to classify individuals as either depressed or not depressed based on a set of features.

Decision Trees are another popular algorithm for classification tasks and can be used in depression detection research to build a decision-making model based on a set of features.

These are just a few examples of the algorithms that can be used in depression detection using machine learning.

ALGORITHMS USED	ACCURACY SUPPORT
VECTOR MACHINE(SVM)	96.10 %
LOGISTIC REGRESSION	96.20 %
RANDOM FOREST	95.10 %
BAYES THEOREM (TFIDF)	88.50%
BAYES THEOREM (BOW)	83.15%

Fig.1 Depression detection Algorithms accuracy in percentage.

VI. PROPOSED SYSTEM

The proposed system for depression detection using ML is a software application that utilizes machine learning algorithms to analyze various sources of data to aid in the detection of depression. The system will take advantage of the ability of ML to analyze large amounts of data and identify patterns that may not be evident to humans. The proposed system will consist of the following components:

A. Data Collection

The system will collect data from various sources, including speech recordings, neuroimaging data, and electronic health records. The data collected will be used to train and validate the ML algorithm.

B. Machine Learning Algorithms

The system will use various ML algorithms to analyze the collected data and identify patterns that are indicative of depression. For example, the system may use natural language processing algorithms to analyze speech patterns or image processing algorithms to analyze neuroimaging data.

C. User Interface

The system will have a user interface that will allow users to input data and receive results. The interface will be user-friendly and intuitive to use.

D. Output

The output of the system will be a prediction of the likelihood of depression. The prediction will be accompanied by a confidence score that indicates the reliability of the prediction.

E. Integration with Clinical Practice

The system will be designed to integrate with clinical practice and aid in the diagnosis and treatment of depression. Mental health professionals can use the system to aid in the diagnosis of depression and provide targeted interventions.

F. Privacy and Security

The system will prioritize the privacy and security of the data collected. The data collected will be anonymized, and access to the data will be restricted to authorized personnel.

VII. CONCLUSION

In conclusion, machine learning algorithms have shown potential in aiding the detection of depression by analyzing various sources of data, including speech, neuroimaging, and electronic health records. The use of ML algorithms in depression detection can potentially lead to earlier diagnosis, targeted interventions, and improved outcomes for individuals with depression. However, there are also limitations and ethical considerations to consider, such as the need for large amounts of quality data and potential biases in the algorithm. Further research is needed to validate the efficacy and safety of ML algorithms in depression detection and ensure their responsible use in clinical practice. Overall, the integration of machine learning in mental health holds promise for improving the accuracy and efficiency of diagnosis, treatment, and research.

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Machine Learning Algorithms for Depression Detection and Their Comparison.

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Abstract —Textual emotional intelligence is playing a ubiquitously important role in leveraging human emotions on social media platforms. Social media platforms are privileged with emotional contents and are leveraged for various purposes like opinion mining, emotion mining, and sentiment analysis. This data analysis is also levered for prevention of online bullying, suicide prevention and depression detection among social media users. In this article we have designed an automatic depression detection of online social media users by analyzing their social media behavior. The designed depression detection classification can be effectively used to mine user's social media interactions and one can determine whether a social media user is suffering from depression or not. The underlying classifier is made using state-of-art technology in emotional artificial intelligence which includes LSTM (Long Short Term Memory) and other machine learning classifiers. The highest accuracy of the classifier is around 70% of LSTM and for SVM the highest accuracy is 81.79%. We trained the classifier on the datasets that are widely used in literature for the emotion mining tasks. Confusion matrix of results is also given.

Keyword---Emotion Artificial Intelligence, Deep Learning, Machine Learning Algorithms, Word Embedding's, Twitter.

I. INTRODUCTION

Depression triggers sorrow, frustration, lack of interest, annoyance. It will contribute to variety of emotional and physical problems and might cut back the power of a person to operate at full potential [1]. The matter of mental state in humans is incredibly serious. At its worst, depression is the main cause of death for 80000 human beings leading them to suicide. Teenagers are most prone to depression as a result of they often need Psychotherapy,

Teenagers limitlessly use mobile phones and social media and spend less time in real world and more in virtuality which causes a gap between their internal state of mind and outward world, causing a strong sense of loneliness which in-turn leads to depression[2]. Bullying via social media based on factors like social status, standard of language, race, ethnicity, immigration standards, health, behavioral ethics, etc. are the main drawbacks of social media which cause depression to user.[4] The definition of problem dealt in this research article is to find whether the person under consideration does have symptoms of depression or not.

With the use of neural networks we have used users tweets to diagnose whether the person under consideration is behaving positively or negatively. If the person is shows particular standard of positivity in his tweets then we can predict him or her to be depression free, otherwise he or she is suffering from depression. The standard used in this article for a person to be considered under depression is that if 80% of his tweets are classified negative. We do the analysis of user feeds posted on a twitter account via state-of-art machine learning and deep learning techniques based on scientifically accepted 80% criterion.[6][7].

1.1. Some Initial Symptoms of depression are listed below:

- Feeling crazy, sad or in a depressing mood
- Weight loss
- Increase fatigue and sleep difficulties.
- Loss of energy and increased fatigue with urge to suicide.
- Thinking very difficultly, concentrating, or making decisions based on the assumption based on the idea of not liking anything.
- Frequent and continuous of death or suicide

Symptoms must last at least two weeks or longer than that. Depression may have a different effect on the sexes and shows that men with depression can have signs such as irritability, escape or dangerous behavior, or that everyone is really angry. Symptoms must last at least two weeks or even more for a diagnosis of depression [1]

1.2. Risk Factors for depression- Depression can affect anyone, even a person who seems to be living in reasonably ideal conditions.

Depression can be caused by a variety of circumstances:

- *Biochemistry:* Harmonal differences may contribute to symptoms of depression in certain cases due to chemicals imbalance in the brain.

- *Genetics:* Genetics also plays an essential role in co-depression for e.g. if one identical twin has depression, for instance, the other has a 70 percent risk of developing the disorder sometime in life.
- *Personality:* People with low self-confidence are more likely to experience depression, causing them to be speechless by stress, or who are generally pessimistic.
- *Environmental factors:* Continuous exposure to violence, negligence, abuse or poverty can make some individuals more susceptible to depression.

1.3. Role of Social Media and Depression

Social networks are becoming an important part of the lives of individuals, they mirror the personal life of the user on social media, people like to share happiness, joy and sorrow [4]. Researchers are using these platforms to classify and detect the causes of depression, reading an old article on the News website about how Twitter can tell if you're depressed and the possibility of developing an artificial intelligence model that can scan your Twitter feed and tell you if an individual is at risk of depression, or accepting notifications from third parties, such as those advising you to seek help based on an automatic scan of your tweets [1]. The day has come to an end. Early detection of depression can be a big step toward addressing the mental illness and providing help to those who are suffering from it. Various approaches for sentiment analysis in Machine Learning, including decision-based systems, Bayesian classifiers, support vector machines, neural networks, and sample-based methods can be used to detect symptoms of depression before it is too late.

II. Depression and Emotion Intelligence

If a person is attached with someone closely then it is clear the person is emotionally attached to that person and if this emotional dependence is too high that the decisions of attached persons are dependent on each other this is called emotion bonding. This is when these persons take emotions seriously sometimes their emotions are not positive in nature hence leading to depression in one or all of them.

2.1. Emotional intelligence is commonly defined by four attributes:

a. **Self-management** – You can control impulsive emotions and actions, handle your emotions in healthy ways, take action, meet commitments, and respond to changing conditions.

b. **Self-awareness** – You recognize your own feelings and how your thoughts and conduct are affected by surrounding conditions. You are aware of your strengths and weaknesses, and have faith and confidence in ones self.

c. **Social awareness** – You've got empathy. You should understand other people's thoughts, desires, and concerns, pick up on emotional signals, socially feel relaxed, and know the dynamics of power in a group or organization.

d. **Relationship management** – You know how to build and maintain good relationships, clearly communicate, inspire and influence others, work well as a team, and resolve conflicts.

III. DISCUSSION

3.1. Dataset

We have developed a depression detection dataset by manually annotating the twitter data. We used two classes for this research one is depressive and other non-depressive. The Tweets were downloads from the twitter Platform and some from the kaggle data and initial dataset had 25,000 tweets from which foreign language tweets and re-tweets were removed. This dataset contains three columns: First Column contains tweet ID, second column contains text and third column contain labels these columns are features. The dataset was then annotated by three annotators and majority voting was kept. Thus if a tweet was annotated depressive by more than one annotator only then it was given a depressive label likewise was done for non-depressive tweets. In the final dataset we had 7,500 depressive tweets and 7,500 non-depressive tweets.

Different algorithms are used we discuss one by one:

3.2. Support Vector Machine (SVM)

Support Vector Machine(SVM) is a supervised algorithm for machine learning that can be used for problems with classification and regression. In classification issues, however, it is mostly used [1]. In the SVM algorithm, we depict each data item as a point in n-dimensional space (where n is the number of characteristics you have), with the value of each

characteristic being the coordinate value. Then, we carry out classification by determining the hyper-plane that clearly distinguishes the two classes [12]. The Support Vector Machine is a discriminative classifier that is formally described by a distinct hyperplane (SVM). In other words, given labelled training data, the algorithm generates an ideal hyperplane that categorizes fresh examples (supervised learning). This hyperplane is a line in two-dimensional space that divides a plane into two sections, with each class on either side. The learning of the hyperplane in linear SVM is finished by changing the issue using some linear algebra [10]. This is when the kernel comes into play. In our experiment we gave the linear SVM using train test split of 80-20%. We employed scikit-learn kernels for the classification purpose.

3.3. Random Forest Classifier

The Random Forest Classifier an ensemble algorithm, produces a set of decision trees from the training set's randomly selected subset. To evaluate the final class of the test object, it then aggregates the votes from various decision trees. Different decision trees can create subsets that overlapping in nature. To deal with this weighting principle is used to consider the impact of any decision tree's result. Trees with a high mistake rate are given a low weight value, whereas trees with a low mistake rate are given a high weight value. Low error-rate trees would have a greater impact on decision-making as a result of this. The total number of trees to be constructed, are as well the important characteristics for the decision tree. The minimum split, split criteria, etc., are all basic Random Forest Classifier parameters. We used Random Forest classifier with 40 estimators. The training and testing sets as inputs to classifier were divided into 80-20 train test splits of total data entries. We employed scikit-learn kernels for the classification purpose as well.

3.4. Multinomial Naïve Bayes

Naive Bayes is a family of algorithms based on applying the Bayes theorem with the strong (naive) assumption that each feature is independent of the others in order to predict the category of a given sample. Because they are probabilistic classifiers, the Bayes theorem will be used to compute the likelihood of each category, and the category with the highest probability will be created. Naive Bayes classifiers have been used successfully in a variety of fields, including Natural Language Processing (NLP).Other options, such as Support Vector Machines (SVM) and neural networks, are available when dealing with NLP issues.

Their simplicity of Naive Bayes classifiers, on the other hand, makes them particularly desirable for such classifiers. Furthermore, they have been proved to be fast, reliable, and exact in a variety of NLP applications. We use a non-naive Bayes approach to look at sentences in their whole, thus if a sentence does not appear in the training set, we will get a zero probability, making further computations impossible. However, in the case of Naive Bayes, each word is assumed to be independent of the others [10]. We now examine individual words as a phrase rather than the complete sentence.

3.5 Long Short Term Memory (LSTM)

LSTMs have proven to be effective in tasks involving sequential knowledge. The input vectors used for the other classifiers, such as the TF-IDF weights vector, do not, however, maintain any information on the sequential relationship between each document's terms and phrases. Thus, the more appropriate input for LSTMs are sequences of word embedding vectors; in fact, word embedding are the preferred option for textual representation in modern deep learning.

We tuned the number of memory units, number of epochs, batch size, and input and recurring dropout rates of LSTM by using the training and tuning set. The number of epochs is the number of times in the neural network the entire training set is moved forward and backward [12]. The network can be fit and the resulting neuron weights may be far from optimal if the number of epochs is too low. Before each change to the weights, the batch size is simply the number of samples fed into the network and helps to make training more effective by reducing the memory requirements and the number of iterations needed to achieve the optimum weights. Finally, in an attempt to minimize overfitting, the dropout rate is simply the likelihood that an input or recurrent node will be omitted from consideration during a weight update. Input to the classifier in the 80-20 train test format was given to the training and testing set respectively.

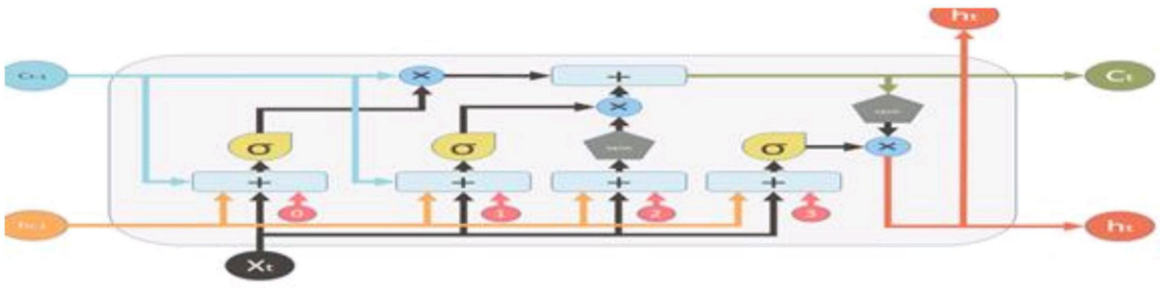

Fig. 1: Mechanism of LSTM Classifier

A cell, an input gate, an output gate, and a forget gate make up a standard LSTM unit. The cell recalls values across arbitrary time intervals, and the three gates govern the flow of information into and out of the cell. Because there might be lags of undetermined duration between critical occurrences in a time series, LSTM networks are well suited to categorizing, processing, and making predictions based on time series data. LSTMs were created to deal with the vanishing gradient problem that might occur when training regular RNNs. The relative insensitivity to gap length of LSTM over RNNs, hidden Markov models, and other sequence learning approaches provides a benefit a variety of applications.

A. LSTM architecture: Multiple architectures of LSTM units exist. The standard architecture consists of a cell (the LSTM unit's memory portion) and three information flow regulators inside the LSTM unit, typically referred to as gates: an input gate, an output gate, and a forgotten gate. Any of the versions of the LSTM device may not have one or both of these gates, or even other gates. Gated Recurrent Units (GRUs) do not, for example, have an output gate. The input gate determines how much a new value enters the cell, the forgotten gate determines how much the cell value remains, and the output gate determines how much the cell value is used to generate the LSTM unit's output activation. The activation function of the LSTM gates is also the logistic sigmoid function.

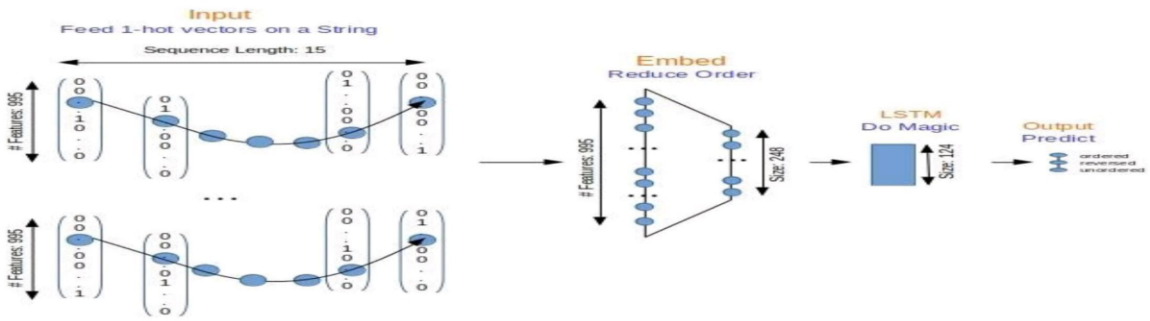

Fig. 2: Process of LSTM

B. Word Embedding

A word embedding is a group of ways for representing words and texts that use a dense vector representation. Instead, in an embedding, words are represented by dense vectors,

each of which reflects the word's projection into a continuous vector space [2]. The placement of a word is based on the words that surround it when it is used and is learned from text inside the vector space. The embedding of a word is its position in the learned vector space. Two common examples of learning methods for embedding words from text include:

- Word2Vec.
- GloVe.

In this Research article Word2Vec and Doc2Vec are used.

C. Keras Embedding layer

Keras provides an embedding layer which can be used on text data for neural networks. This includes integer encoding of the input data, so that each word is represented by a unique integer. The Tokenizer API that is also supplied with Keras can be used to perform this data preparation stage. All of the words in the training dataset will learn an embedding since the Embedding layer is initialized with random weights. It's a versatile layer that can be applied in a variety of ways, like it can be used on its own to teach a word integration that can then be stored and reused in a different model. It can be utilized as part of a deep learning model where the embedding is taught alongside the model. It is a type of transfer learning, and can be used to load a pre-trained word embedding model. Weights are learned in the Embedding layer. If you save your model as a file, the weights for the Embedding layer will be included. An embedding layer's output is a 2D vector in the input word sequence (input document), with one embedding for each word. You must first flatten the 2D output matrix to a 1D vector if you want to link a dense layer directly to an embedded layer using the *Flatten* layer. Finally we train the LSTM Classifier for training and testing data classification.

IV. METHOLODOLOGY

In this section we discuss the overall methodology that is used for depression detection using online social profiles of the user. We employ emotional artificial intelligence for the depression detection task. We create a depression classifier using Deep-Learning framework and machine learning and use that classifier for classifying tweets from an online social

profile for automatic depression detection. Figure 5 shows the overall methodology used for the task.

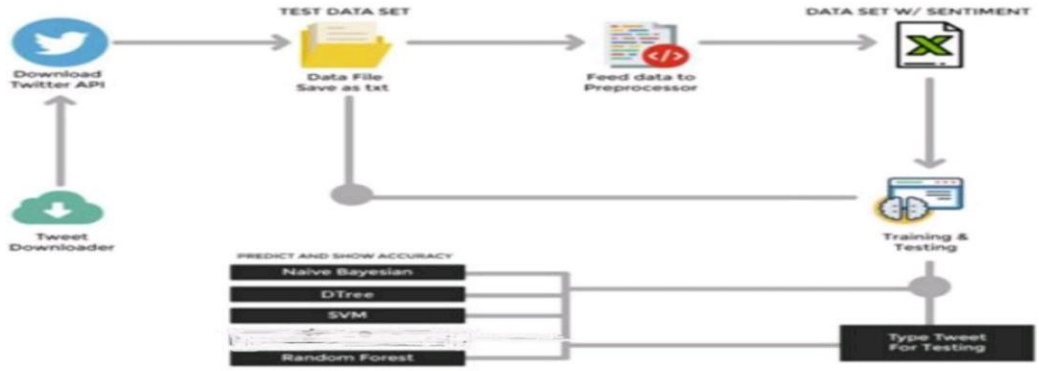

Fig. 3: Overall methodology of the depression detection system.

The system receives as input an emotion labeled dataset which is used for the training of supervised deep-learning classifier or machine learning classifier. Once the classifier is trained on emotion labeled dataset we use the tweets from online social profiles for the depression detection. If the tweets from the profile contain more than 75% tweets classified as depressive, our system classifies gives the red flag for the profile that it may be having depression symptoms. Figure 6 shows the components of the system in detail.

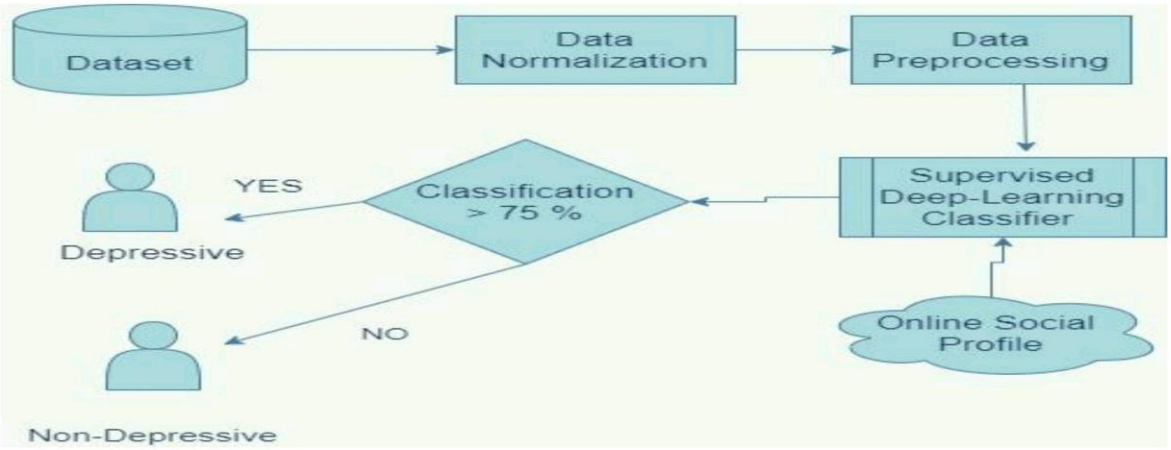

Fig. 4: Architecture of the system

The system has 5 modules and uses emotion labeled dataset.

4.1. Data Normalization

As part of data preparation for machine learning, standardization is a technique sometimes used. The aim of adjustment is to adjust the numeric column values in the dataset to use a common scale, without distorting disparities in the value ranges or losing information. You also deleted all retweets, all non-alphanumeric characters, URLs, and @mentions. Besides, all stop words were abolished, with the exception of first, second and third person pronouns. About 40% work done by this through NLTK automatically and all libraries.

4.2. Data Preprocessing

Preprocessing each tweet before passing it to the automated classifier is how the preprocessing module prepares it for the classifier. Slangs and abbreviations are eliminated by the use of English directories from the tweets. If a term is identified that does not have a meaningful definition, all of the words are passed into the dictionary module to be looked up, and then into the word replacer module to be replaced with the right word. In the word replacer module, we employed the SMS dictionary, Netlingo, and the urban dictionary. Preprocessing stages are made up of the following steps:

4.3. Tokenization

Is performed using Stanford Core NLP package to break tweets into sentences and words, such as units of words, sentences, or themes? The first column of the csv file containing the tweet is extracted and converted to individual tokens in this case.

4.4. Stemming

Stemming is the process of reducing words to their simplest form. This would allow us to group terms that are similar together. Poster Stemmer is utilized for implementation.

4.5. Stop Words Removal

Because they are of little use in training, the widely used words known as stop words need to be omitted and may also lead to incorrect results if not ignored. There is a collection of stop words in the NLTK library which can be used as a guide for removing stop words from the dataset. Stop words that are deleted from tweets using the Tf-Idf, Stanford, and wiki features.

4.6. POS Tagger

The tokenized text is allocated to the respective sections of the speech by using a POS tagger to improve the quality of the remaining data. Since other parts of speech are not of much importance, this can be used to remove only adjectives, nouns and adverbs. Example: 'I LOVE CODING' is extracted-'I 'is a pronoun, rest is omitted.

4.7. Lemmatization

It's used to apply stem words to their stems. Lemmatization refers to performing things correctly utilizing a vocabulary and morphological word analysis, mainly aimed at merely removing inflectional endings and restoring the root or dictionary form of a word known as the lemma, utilizing the Stanford core NLP kit.

A bag of words is generated after all of these pre-processing stages. The number of occurrences of each word is calculated in a bag of words, which is subsequently utilized as a feature to train a classifier.

4.8. Bag of words or One Hot Encoding

Each part of the vector corresponds to one word or n-gram (token) within the corpus vocabulary during this methodology. Then if the token at a selected index exists within the document, that part is marked as one, else it's marked as zero.

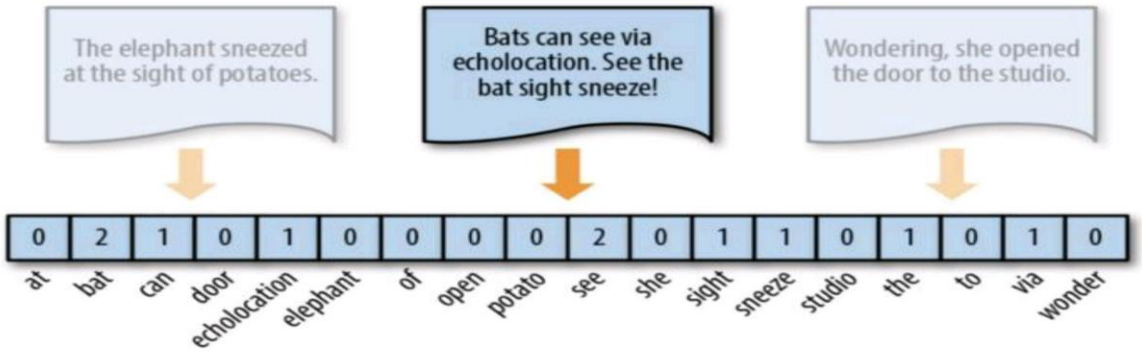

Fig.5: BOW Representation

In the above example, our corpus consists of every unique word across the three documents. A bag of Words model, or BOW for short, is a method of extracting text properties for use in modeling, such as machine learning techniques. The method is straightforward and adaptable,

and it may be used to extract information from documents in a variety of ways. A bag of words is a text representation of the words that appear within a document.

It involves two ways:

1. A vocabulary of known words.

2. The measure of the presence of known words should be considered.

It's dubbed a bag of words because all information in the text about the sequence or arrangement of words is discarded. The model simply considers where recognized phrases appear in the document, not where they exist in the document. The histogram of the words inside the text is examined in this method. The bag of words approach (BOW), which considers each word count as a function, is a popular role extraction method for sentences and texts. The assumption is that documents are similar if they have comparable content. Furthermore, we can deduce something about the document's significance solely from its content. You can make the word bag as simple or as complex as you desire. The difficulty arises from deciding how to create the lexicon of knows words (or tokens) as well as how to rate the presence of such words.

4.9 Term Frequency-Inverse Document Frequency

TF-IDF stands for term frequency-inverse document frequency. It's a statistical metric for determining how important a word in a corpus of documents is to a text. This importance is related to the number of times a word appears in the text, but is offset by the number of documents in the corpus that contain that word.

4.10 Count Vectorization

The number of occurrences in a document for each word (i.e. independent text, such as an article, book, or simply a paragraph!) can be tallied using Count Vectorization. The Sci-kit learning library in Python offers a tool called CountVectorizer that can help with this. "The weather was nice today, so I went outdoors to enjoy the gorgeous and sunny weather," for example. The words "the," "weather," and "and" all appeared twice in the performance below, whereas other words only appeared once. Count Vectorization achieves this goal.

4.11 Distributional Similarity Based Representations- Word Embedding's

A word embedding may be a sort of learnt text illustration (real valued vectors) during which words with connected meanings square measure drawn equally, like the favored "King-Man + girl = Queen" example. For every word, the idea of employing a dense, distributed illustration is central to the approach. Every term may be a real-value vector with tens or many dimensions. In distinction, distributed word representations, like one-hot encryption, need thousands or countless dimensions. The 2 most well liked word embedding's square measure Word2Vec and Glove:

4.12. Word2Vec:

There square measure primarily 2 versions of Word2Vec — Skip-Gram and Continuous Bag of Words (CBOW). The embedding is learned by the CBOW model anticipating the present word supported its context (surrounding words). Given a current word, the Skip-Gram model learns by predicting the encompassing words (context). Word2vec represents every separate word with a selected list of numbers referred to as a vector, because the name suggests. The vectors square measure a basic function (the similarity of the trigonometric function between the vectors) is employed. Indicates the amount of linguistics similarity between the words drawn by those vectors. Skip-gram seeks to predict a given word's immediate neighbors. We tend to take a central word and a context window (neighbors) terms, and take a few window step sizes round the central word, we tend to attempt to predict the context words. So, our model can describe a distribution of chance, i.e. the chance of a word occurring in context given a central word, and to maximize the chance, we'll select our vector representations. We tend to take away the output layer and use the hidden layer to urge our word vectors till we are able to predict the encompassing words with an affordable degree of exactitude. We tend to begin with little random data formatting of vectors of terms. By minimizing the loss perform, our prognosticative model learns the vectors. In Word2vec, this happens with a feed-forward neural network with a language modeling task (predict next word) and improvement techniques like random gradient descent. This measures the options that I actually have used for machine learning algorithms like SVM, Naïve Thomas Bayes, and Random Forest.

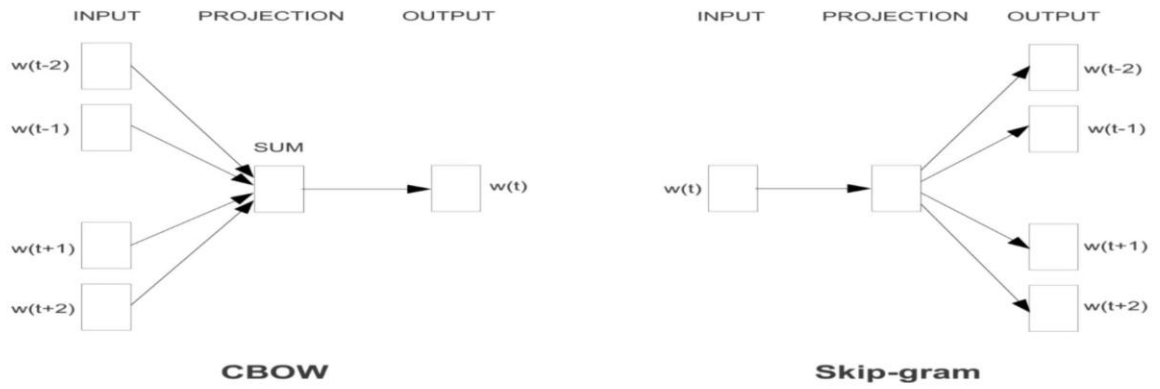

Fig. 6: Word2Vec CBOW vs Skip-gram

4.13. Gensim Model for DOC2VEC used in LSTM

Gensim is paid as a kit of natural language processing that 'Topic Modeling for Humans' does. But it's even more than that, technically. I used Doc2Vec for LSTM, meaning the model of a deep learning algorithm, so clarify Doc2Vec first. I have already mentioned the Word2Vec I used in machine learning algorithms since I used algorithms for machine learning as well as deep learning algorithms. So, for machine learning, I used Word2Vec and I used Doc2Vec for the LSTM model. The aim of doc2vec, regardless of its length, is to construct a numeric representation of a text, as mentioned. But records do not come in logical forms like words and unlike words, so another technique needs to be found. Because the Doc2vec model is an unsupervised process, it should be slightly adjusted to "participate" in this challenge. Fortunately, as in most circumstances, we can utilize a couple tricks: remember how we introduced another document vector in fig 3 that was unique to each document? If you think about it, you can add more vectors that don't have to be unique: for example, if we have tags for our documents (which we have), we can add them and receive their representation as vectors.

Additionally, they don’t have to be unique. This way, we can add to the unique document tag one of our 17 tags, and create a doc2vec representation for them as well! See below:

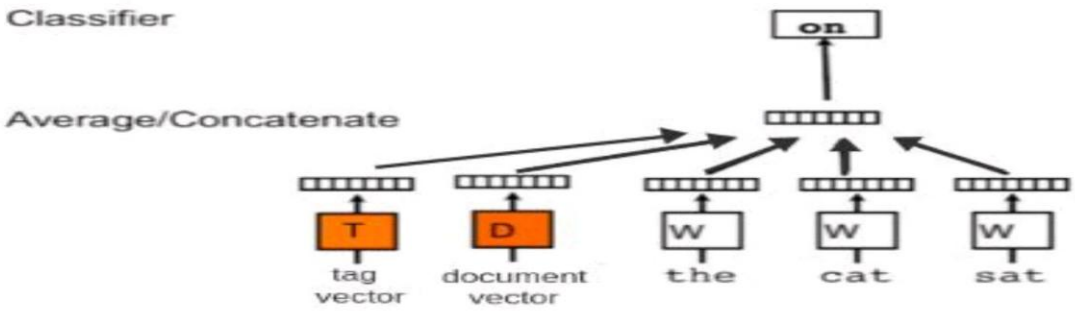

Figure. 8: Doc2Vec model with tag Vector

4.14. Training

From the training set both label and tweet are required by the classifier. The training set in this example refers to the set of tweets that must be processed before being fed into a classifier. The set of tweets must be transformed to a vector representation for further processing. The set of labels corresponding to each tweet is also provided into the classifier as a vector.

4.15. Saving the classifier and the count vectorizer object

Since training needs to be done once, it is necessary to load the trained classifier object into a pickle file. Same is applicable with the count Vectorizer Object. It count the number of words present in the pickle file using the TF-IDF method. And then the testing phase takes place for unseen data.

4.16. Testing

Loading of saved models: Qualified classification models are loaded from the pickle file to be used for test dataset prediction (Individual tweet profiling data). The test dataset is preprocessed in a way that is similar to the data from the training for test tweets class prediction. Each tweet is graded into a class that is depressed or non-depressed. We calculate the confusion matrix for the assessment of classification results based on the values of true or false positives and negatives. Confusion Matrix is used for how much our classifier shows accurate results as well as false results.

V. RESULTS

The depression detection system that we designed uses emotional artificial intelligence for the detection of depression using online social profiles. We used supervised learning models

and Deep Learning algorithm i.e Long Short Term Memory (LSTM) were training of the classifier was given using the emotion dataset. The dataset has 15,000 tweets manually annotated by us. The highest accuracy of the classifier is around 70% for LSTM and for SVM the highest accuracy is 81.79%. I have trained the classifier on the datasets that are widely used in literature for the emotion mining task. The results are presented using the classification metrics like accuracy and confusion matrix.

Confusion Matrix: A confusion matrix is a machine learning classification performance evaluation methodology. It's a type of table that allows you to see how well a classification model performs on a set of test data for which the true values are known. True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) these given four parameters of the confusion matrix are used to calculate the Accuracy, Recall, Precision and FI-Score, with the help of these four classes we compute all values. The results are evaluated on the basis of F1 score and accuracy. The F1 score is the primary performance measure and accuracy is the secondary measure with the help of confusion matrix we call Precision, Recall, F1 Score and Accuracy it simply shows how much our classifier shows accurate results or with the help of given formulas:

A. Precision: TP/TP+FP, where TP is true positive, FP is false positive.

B. Recall: TP/TP+FN.

C.FI Score: 2* (Precision*Recall)/ Precision + Recall

The dataset was balanced having 7,500 tweets in each data class that is depressive and non-depressive. SVM classifier its accuracy is more than other classifiers. We choose SVM classifier for unseen data. We trained our system using LSTM (Deep Learning Classifier), SVM, Naïve Bayes and Random Forest classifier (Machine Learning Classifier). The classifiers accuracy is described in the below table:

Classifier	Precision	Recall	F1 Score	Accuracy
LSTM	0.88	0.60	0.71	70.00%
Multinomial NB	0.79	0.78	0.78	79.32%
SVM	0.79	0.82	0.79	81.79%
Random Forest	0.75	0.82	0.78	80.37%

Table 1 Results of different Classifier performance

Figure 9, 10, 11 and 12 show the performance of the system using confusion matrices:

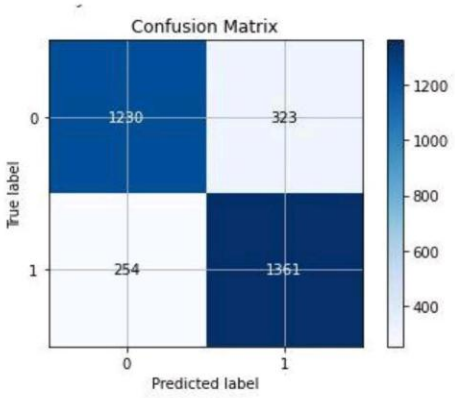

Fig. 9: Confusion Matrix of SVM

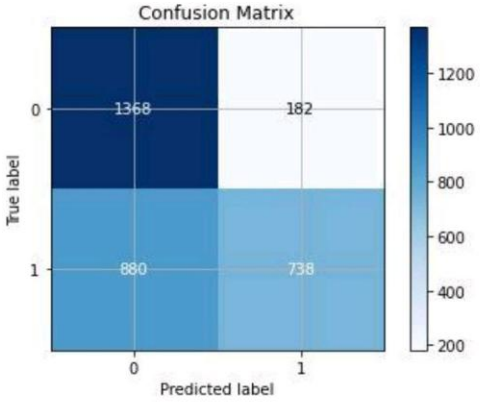

Fig.10: Confusion Matrix of LSTM

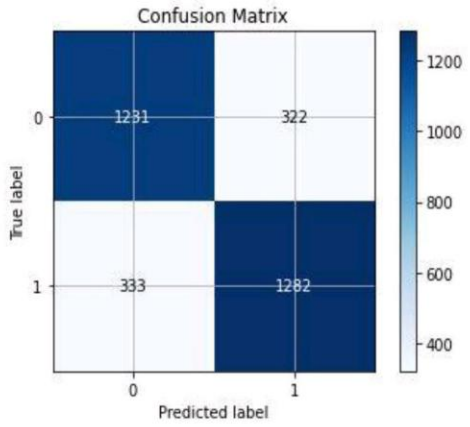

Fig.10: Multinomial Naïve Bayes

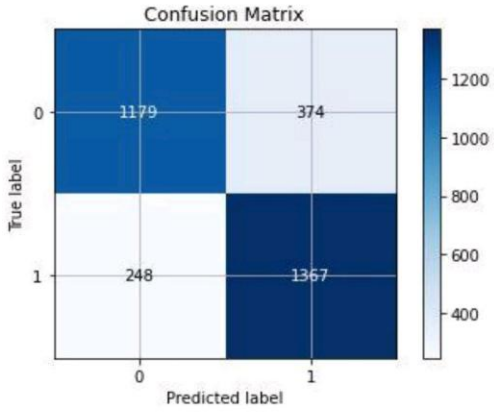

Fig. 12: Random Forest

V1. CONCLUSION AND FUTURE WORK

The analytics performed on the chosen dataset offer some insight into the analysis issues. The subsequent may be an outline of our findings: What is depression, and what area unit the foremost current causes of depression? whereas we have a tendency to all feel irritable, unhappy, or low from time to time, some individuals experience these feelings on an

everyday basis, over long periods of your time (weeks, months, or perhaps years), and in some cases for no obvious cause. Despondence is over simply a nasty mood; it is a state of affairs that has a bearing on an individuals physical and mental well-being. Any one can be suffering from depression at any time. However, bound stages or circumstances in modern day world expose people to anxiety and depression. During entire life the changes around or inside an individual all end in a surge of emotions which will contribute to unhappiness in introvert and socially separated people. We conducted a comparison of state-of-art deep learning models to pre-detect depression from tweets at the user level. We ran our models on a manually preprocessed dataset and discovered that SVM created higher results. In the future, we can use a special methodology to extract paraphrases from a wider set of emotional qualities. We will additionally check the quality and potency of our models with lot more datasets.

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Appendix B: Research Paper

Int. J. Eng. Res. & Sci. & Tech. 2025

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 21, Issue 2, 2025

A Unified Framework for Depression Detection Using ML Algorithms

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Abstract:

Depression is a common mental health disorder that greatly impacts a person's quality of life and productivity. With the rise of social media and digital communications, analyzing textual data for mental health insights has gained considerable attention. This study presents a comparative analysis of traditional Machine learning algorithms—such as Random Forest, Bagging, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes. Textual data is preprocessed and vectorized before being fed into the machine learning models, Evaluation is carried out using performance metrics such as accuracy, precision, recall, and F1-score.and compare the models. Experimental results indicate that logistic regression and navie bayes machine learning models Achieve higher accuracy compared to traditional techniques and contextual understanding. This study highlights the potential methods for robust and scalable depression detection systems.

Key Words: Random Forest, Logistic Regression, Support Vector Classifier (SVC) ,Naive Bayes ,Bagging Classifier , Machine Learning.

Introduction:

Depression is a widespread and debilitating mental health disorder, affecting over 280 million people globally. Defined by persistent sadness, lack of interest, and cognitive challenges, it not only impacts individual well-being but also carries significant societal and economic costs. Early detection is crucial for effective treatment, yet traditional diagnostic methods—relying on self-reported symptoms and clinical assessments—are often time-consuming, subjective, and inaccessible for many.

With the rise of digital communication, especially on social media, large volumes of user-generated text present new opportunities for analyzing mental health indicators. Natural Language Processing (NLP) and machine learning (ML) techniques can leverage these data sources to detect signs of depression through linguistic patterns and semantic cues.

This study compares several machine learning algorithms—including Random Forest, Bagging, Support Vector Classifier (SVC), Logistic Regression, and Naive Bayes—for detecting depression from text

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 21, Issue 2, 2025

data. We evaluate these models based on accuracy, precision, recall, and F1-score to assess their effectiveness. The goal is to contribute to the development of automated tools that support early diagnosis and timely intervention in mental health care.

1.1 Need Of Detecting Mental Health:

Rising Mental Health Concerns: Depression is a leading cause of disability worldwide, with increasing prevalence, especially in the post-pandemic era. Early detection can significantly improve outcomes.

Lack of Clinical Resources: Mental health professionals are limited; automated tools can assist in early screening, Alleviating the strain on healthcare systems.

Data-Driven Insights: Machine learning (ML) and deep learning (DL) models can uncover hidden patterns in text or behavioral data that may be overlooked in traditional diagnostics.

Improved Accuracy: Combining ML algorithms like Random Forest, SVC, and Logistic Regression can enhance detection accuracy through complementary strengths.

Scalability: Automated systems are capable of processing large amounts of data rapidly, making them perfect for large-scale mental health monitoring (e.g., social media screening, surveys).

1.2 Identified Research Gaps:

Limited Integration of Traditional ML and Deep Learning Approaches:

Most existing studies use either traditional ML (e.g., Logistic Regression, Random Forest) or deep learning (e.g., BERT), but not both in a hybrid framework. A combined approach could improve robustness and accuracy.

Underutilization of BERT for Mental Health Detection:

Although BERT and transformer-based models have shown promise in NLP tasks, their application in depression detection is still emerging and often not compared directly with classical ML techniques.

Lack of Benchmarking Across Diverse Algorithms:

Few studies provide a comprehensive comparison between multiple classifiers (e.g., Bagging, SVC, Naïve Bayes) and advanced deep learning models under the same conditions or datasets.

Inconsistent Datasets and Evaluation Metrics:

Studies often use different datasets (e.g., social media posts, clinical text) without standardization, making it hard to assess model generalizability. There's also a lack of uniform performance metrics like F1-score, precision, and recall, especially in imbalanced datasets.

Lack of Explainability in Deep Learning Models:

BERT-based models often act as "black boxes." There is a need for interpretable models or methods to visualize how decisions are made, especially in sensitive applications like mental health.

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Neglect of Multilingual and Cross-Cultural Analysis:

Most models are trained on English data, ignoring linguistic and cultural nuances in how depression is expressed in different regions or languages.

Literature Review:

Depression detection using Natural Language Processing (NLP) and machine learning (ML) has gained increasing attention as researchers explore non-invasive, scalable methods for mental health assessment. Early studies primarily relied on manually crafted linguistic features, such as word frequency, sentiment scores, and psycholinguistic markers, extracted from written text to differentiate between depressed and non-depressed individuals (Pennebaker et al., 2003). Tools like the Linguistic Inquiry and Word Count (LIWC) have been widely used to quantify psychological and emotional cues in language.

Multiple machine learning algorithms have been applied to classify depression-related content. For example, Resnik et al. (2015) utilized Support Vector Machines (SVMs) to classify posts from mental health forums, achieving promising results through a combination of lexical and semantic features. Similarly, Coppersmith et al. (2014) demonstrated that features derived from Twitter posts could predict depression with reasonable accuracy using classifiers such as Logistic Regression and Naive Bayes. Their work highlighted the potential of social media data in identifying mental health conditions outside clinical settings.

Random Forest and ensemble methods like Bagging have also been explored for their robustness and ability to handle high-dimensional textual data (Shen et al., 2017). These models often outperform single classifiers by reducing variance and improving generalization. However, traditional ML models depend heavily on feature engineering, which can be time-consuming and may fail to capture deeper linguistic nuances (Calvo et al., 2017).

Other studies have compared the performance of different classifiers. Tsugawa et al. (2015) compared Naive Bayes, Logistic Regression, and SVM for detecting depressive tendencies on Twitter, noting that classifier choice, feature selection, and preprocessing significantly influenced performance metrics such as precision and recall.

Despite their limitations, traditional machine learning approaches remain valuable due to their interpretability and lower computational requirements compared to deep learning models. They also offer a practical baseline for developing automated systems for depression detection, particularly when resources or annotated data are limited.

In summary, the literature shows a consistent interest in leveraging textual data and machine learning algorithms—such as SVM, Random Forest, Logistic Regression, Naive Bayes, and Bagging—to detect depression. While accuracy varies depending on datasets and features, these approaches provide a foundation for

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ISSN 2319-5991 www.ijerst.com
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building scalable mental health monitoring tools.

2.Problem Statement:

Depression is a growing global health concern, yet early and accurate detection Continues to be a challenge because of the subjective nature of symptoms and the lack of mental health resources professionals. While machine learning (ML models have shown potential in automating the detection process, most existing approaches rely exclusively on either traditionalML.Furthermore, inconsistencies in evaluation methods, dataset limitations, and a lack of interpretability in deep learning models hinder the practical deployment of these systems. Therefore, there is a critical need to develop a hybrid approach that combines traditional machine learning techniques (such as Random Forest, Bagging, SVC, Logistic Regression, and Naïve Bayes) to improve the accuracy, scalability, and explainability of automated depression detection systems.

3.Related Work

Several studies have explored The application of machine learning and deep learning for identifying depression, especially from text data like social media posts, survey responses, or clinical notes.

1. Traditional Machine Learning Approaches:

Previous research has applied models such as Logistic Regression, Naïve Bayes, Support Vector Machines (SVM), and Random Forest to classify depression based on text features like n-grams, TF-IDF, and sentiment scores. For example, Resnik et al. (2015) used linguistic features from Reddit posts to detect depression, while Tsugawa et al. (2015) applied SVMs on Twitter data with user behavior metrics. While these models are interpretable and efficient, they often struggle with understanding contextual nuances in language.

2. Ensemble Methods:

Studies have shown that ensemble techniques like Bagging and Random Forest can improve prediction stability and reduce overfitting in depression detection tasks. These methods combine the outputs of multiple base learners, enhancing generalization on unseen data. However, they still rely heavily on manually engineered features.

3. Hybrid Models and Comparative Studies:

There is limited work that directly compares or combines traditional ML classifiers with BERT models for depression detection. Most comparative studies evaluate models in isolation, making it difficult to determine the optimal method or synergy between techniques.

4. Challenges in Datasets and Evaluation:

Many studies use imbalanced datasets, which can lead to biased predictions. Additionally, inconsistencies in metrics (e.g., accuracy vs. F1-score) and dataset domains (social media vs. clinical text) complicate comparisons across studies. Some researchers have called for more standardized benchmarks and explainable AI techniques to enhance real-world applicability.

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4.Proposed Work

The proposed approach seeks to develop a hybrid framework for automated depression detection that combines traditional machine learning algorithms with deep learning models like BERT. This framework will leverage the strengths of both approaches to improve accuracy, robustness, and interpretability in classifying depressive symptoms from textual data (e.g., social media posts, questionnaires, or clinical notes).

1. Data Collection and Preprocessing

Collect publicly available datasets (e.g., Reddit, Twitter, DAIC-WOZ, or clinical depression corpora).

Preprocess the text by eliminating stop words, punctuation, URLs, and other irrelevant elements, and applying lemmatization.

Label the data based on depressive vs. non-depressive content (either manually or using dataset annotations).

2. Feature Extraction for Traditional Models

Extract features such as:

TF-IDF vectors

These features will be used as inputs to traditional classifiers.

3. Model Training – Traditional Machine Learning

Implement and compare the performance of:

Logistic Regression

Naïve Bayes

Support Vector Machine (SVC)

Random Forest

Bagging Classifier

Use stratified k-fold cross-validation for reliable performance measurement.

4. Hybrid Evaluation Framework

Compare Evaluate the performance of all models using standard metrics: Accuracy, Precision, Recall, F1-score, and AUC.

Investigate hybrid strategies, such as:

Model ensembling (e.g., majority voting or stacking of ML and BERT predictions)

Confidence-based fusion (e.g., choose prediction from model with higher confidence)

5. Model Interpretability

Use tools such as LIME or SHAP to explain model decisions, especially for deep learning models.

Analyze important features or attention weights contributing to depressive classification.

5.Implementation:

mental health detection using the specified machine learning and deep learning frameworks, presented as descriptive matter without any code**.**

Goal: Implement a system to detect indicators of mental health distress from text data.

General Steps for Any ML/DL Project:

Data Collection: Acquire a dataset consisting of text samples (e.g., social media posts, forum comments, clinical

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notes) that are labeled with relevant mental health categories (e.g., 'distressed', 'not distressed', or specific conditions like 'depression', 'anxiety').

Data Preprocessing: Clean the text data. This typically involves steps like:

Handling missing values.

Removing noise (HTML tags, special characters, URLs).

Lowercasing text.

Tokenization (dividing text into words or sub-word units).
Eliminating stop words (frequent words such as 'the', 'a', 'is').
Stemming or lemmatization (reducing words to their base form).

Feature Engineering/Representation: Convert the cleaned Converting text into a numerical format that machine learning models can interpret. This step varies considerably between traditional ML and deep learning.

Model Selection: Choose one or more algorithms appropriate for text classification.

Training: Use the labeled training data (text features and their corresponding labels) to train the chosen model(s).
Evaluation: Measure the performance of the trained model(s) on unseen test data using relevant metrics.

Prediction: Deploy the trained model to classify new, unlabeled text data.

Traditional Machine Learning Frameworks (scikit-learn):

Frameworks Covered: Logistic Regression, Naive Bayes, Support Vector Machine (SVM), Random Forest, Bagging Classifier.

Feature Representation: Traditional ML models cannot process raw text. Text must be converted into numerical vectors. Common techniques include:

Bag-of-Words (Count Vectorization): Represents a document as a vector, with each dimension corresponding to a word in the vocabulary, and the value indicating the frequency of that word in the document.

TF-IDF (Term Frequency-Inverse Document Frequency): Similar to Bag-of-Words, but adjusts word counts based on their significance across the entire dataset, lowering the weight of extremely common words.

More advanced: Using pre-trained word embeddings (like Word2Vec, GloVe) and aggregating them (e.g., averaging) to represent documents.

Model Training:

Initialize the chosen model (Logistic Regression, Multinomial Naive Bayes, SVC, RandomForestClassifier, BaggingClassifier).

Train the model on the numerical feature representations of the training text (X_train_features) and their corresponding labels (y_train).
Evaluation:
Use the trained model to predict labels for the numerical feature representations of the test text (X_test_features).
Compare the predicted labels (y_pred) with the actual test labels (y_test).
Compute standard classification metrics such as accuracy, precision, recall, and F1-score using scikit-learn tools.

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Key Considerations:

Performance heavily relies on the chosen feature engineering technique and its parameters.

Hyperparameter tuning for each model is essential to achieve optimal performance.

Naive Bayes (specifically Multinomial Naive Bayes) is often a strong baseline for text classification.

Ensemble methods (Random Forest, Bagging) can improve robustness.

Feature Representation: BERT handles text representation internally.

Tokenization: Text is broken down into sub-word units using a specific tokenizer corresponding to the pre-trained BERT model (e.g., BertTokenizerFast). Special tokens ([CLS], [SEP]) are added, and sequences are padded or truncated to a fixed maximum length (max_len).

Input Formatting: The tokenizer outputs numerical representations required by BERT, including input_ids (token indices), attention_mask (indicating real tokens vs. padding), and potentially token_type_ids.

Calculate standard classification metrics (accuracy, precision, recall, F1-score).

General Considerations for Mental Health Detection Systems:

Data Quality and Ethical Sourcing: Obtaining high-quality, accurately labeled text data is crucial and presents significant ethical challenges regarding privacy, consent, and data origin.

Ethical Implications and Bias: Deploying such systems requires careful consideration of potential biases in the training data that could lead to unfair predictions for certain demographic groups. The primary goal should often be to flag content for human review, not to make automated diagnoses. Transparency and user consent are vital.

Nuance and Context: Human language expressing distress is complex, context-dependent, and highly variable. Models need to be robust enough to handle this complexity.

Evaluation Metrics: Depending on the application's risk tolerance, different metrics might be prioritized. For instance, in a system aiming to identify individuals needing help, recall (minimizing false negatives) might be more important than precision.

Explainability: Understanding why a model made a particular prediction can be important, especially in sensitive applications. This is generally easier with traditional models but techniques are emerging for explaining deep learning predictions.

.Algorithms used :

6.1 Liner SVC:

Linear Support Vector Classifier Linear SVC is a robust and commonly used machine learning algorithm for binary text classification tasks, making it highly suitable for depression detection. In this context, it is employed to categorize text data—such as social media posts or clinical notes—into "depressed" and "non-depressed" categories. A key advantage of Linear SVC is its ability to effectively manage high-dimensional feature spaces, which are typical in text data after techniques like TF-IDF or n-gram

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ISSN 2319-5991 www.ijerst.com
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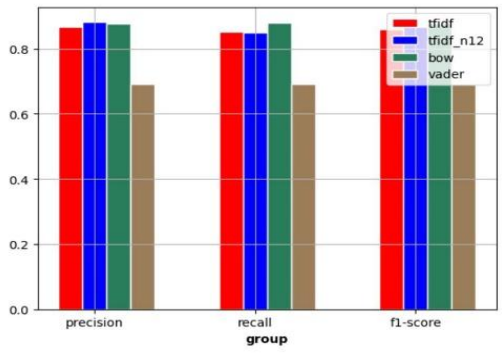
vectorization. It is computationally efficient and scales well with large datasets, enabling it to process thousands of text entries quickly. The model also features a regularization parameter that aids in handling overfitting.

prevent overfitting, which is crucial when working with real-world, noisy data. Linear SVC fits well into the proposed hybrid framework as a traditional machine learning baseline and offers a strong benchmark for performance comparison against more complex models like BERT. However, it assumes that the data is linearly separable and may not perform as well when deeper contextual understanding is required—something that transformer-based models like BERT can better capture. Despite this, Linear SVC remains a valuable component of the overall system due to its simplicity, speed, and effectiveness in many depression detection scenarios.

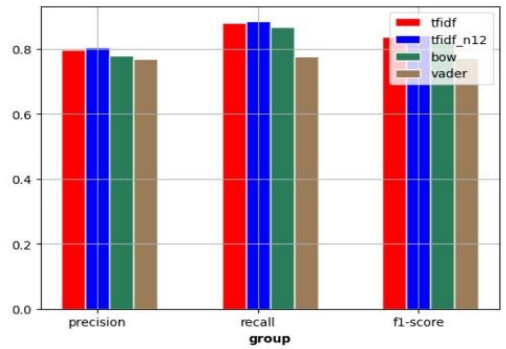


6.2Random Forest:

Random Forest is an ensemble machine learning algorithm that can be effectively applied to depression detection in text data.

It functions by constructing multiple decision trees during training and aggregating their outputs—usually through majority voting—to generate final predictions. This method enhances accuracy and reduces the likelihood of overfitting compared to relying on a single decision tree. In the context of depression detection, Random Forest performs well with structured features derived from text, such as TF-IDF vectors, sentiment scores, or linguistic indicators. It is especially resilient to noise and adept at capturing complex, non-linear relationships within the data. Additionally, it provides feature importance scores, which can help identify the words or patterns most indicative of depression.

depressive language. While it may not capture contextual language as deeply as deep learning models like BERT, Random Forest serves as a strong and interpretable traditional machine learning baseline in a hybrid framework. It is especially useful when working with medium-sized datasets and offers a good balance between accuracy, interpretability, and computational efficiency.



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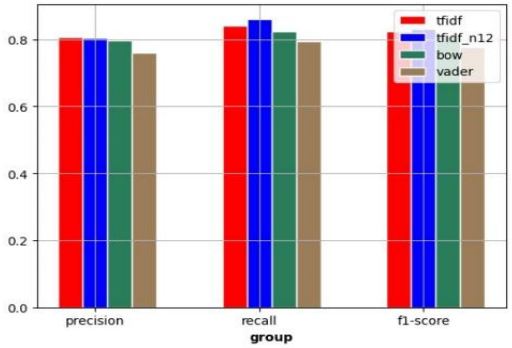
6.3Bagging(Bootstrap Aggregating):

Bagging, short for Bootstrap Aggregating, is an ensemble learning method that enhances the stability and accuracy of machine learning models, especially when working with high-variance algorithms. In the context of depression detection, Bagging can be used with classifiers such as Decision Trees or Random Forests to boost performance. The core concept of Bagging involves generating multiple subsets of the original training dataset by sampling with replacement (bootstrapping), then training a separate model on each subset. Final predictions are made by combining the outputs of all individual models, typically using voting in classification tasks.

In the case of depression detection, Bagging helps mitigate the risk of overfitting by combining predictions from multiple models, leading to a more generalized classifier. This is especially valuable when working with noisy or imbalanced data, which is common in real-world text datasets. Bagging is relatively simple to implement and does not require fine-tuning of many hyperparameters. While it might not capture deep contextual meaning in text, it excels in improving accuracy and robustness when used with base classifiers like Decision Trees or Random Forests. Its ability to handle large, complex datasets with varied feature distributions makes it a useful addition to the traditional machine learning pipeline for depression detection, contributing to a hybrid framework that combines multiple techniques for improved results.



6.4 Logistic Regression:

Logistic Regression is a fundamental and widely adopted algorithm for binary classification tasks, making it well-suited for depression detection, where the objective is to classify text as either “depressed” or “non-depressed.” It estimates the probability that a given input belongs to a specific class using the logistic (sigmoid) function. In this project, once textual data is transformed into numerical features through methods like TF-IDF or word embeddings, Logistic Regression can efficiently learn the association between these features and the target labels.

Despite its simplicity, Logistic Regression Performs unexpectedly well in text classification tasks because of the linear separability of the data high-dimensional text features.

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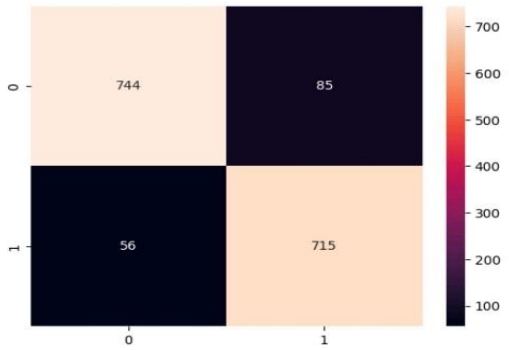
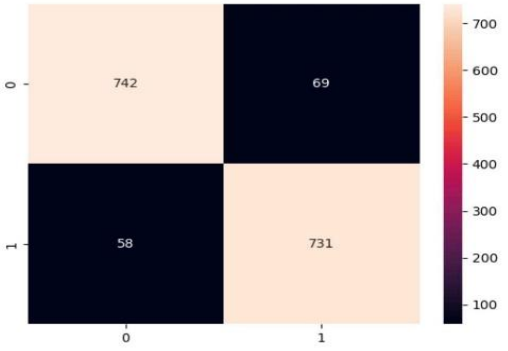


6.5 Navie bayes:

Naïve Bayes is a probabilistic machine learning algorithm grounded in Bayes' Theorem and is particularly effective for text classification tasks such as depression detection. In this project, Naïve Bayes can be used to classify text data—like social media posts or written survey responses—into "depressed" or "non-depressed" categories. The model operates under the assumption that features (usually words or tokens) are conditionally independent given the class label, which simplifies computation and enables rapid training, even on large datasets.

Despite its "naïve" assumption of feature independence, Naïve Bayes often delivers surprisingly strong performance in text classification due to the fact that this assumption tends to work well with sparse, high-dimensional data such as TF-IDF vectors. It is especially advantageous when working with imbalanced datasets or under limited computational resources. In the context of depression detection, Naïve Bayes can efficiently uncover linguistic patterns that signal depressive symptoms. However, a key limitation is its inability to capture complex relationships or word dependencies.

context—something that deep learning models like BERT handle much better. Still, Naïve Bayes serves as a strong and interpretable baseline in the traditional machine learning pipeline, offering speed, simplicity, and reasonable accuracy, especially when combined in ensemble strategies within a hybrid framework.



7.Comparing methods:

To compare Bagging, Random Forest, Linear SVC, Logistic Regression, Naive Bayes, and BERT for depression detection, we need to consider various aspects such as their algorithmic nature, performance, interpretability, data requirements, and suitability for text-based tasks (since depression detection often involves textual data like social media posts, survey responses, or clinical notes).

7.1. Bagging (Bootstrap Aggregating)

- Type: Ensemble (ML)
- Description: Combines multiple base learners (often decision trees) trained on different bootstrapped subsets.
- Pros:
    - Reduces variance, helps prevent overfitting.

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- Performs well on smaller datasets.

- Cons:
  - Less interpretable.
  - Not specifically optimized for text.
- Use in Depression Detection:
  - Can be applied after extracting features (e.g., TF-IDF, word embeddings).
  - Less commonly used than more specialized models.

7.2. Random Forest

- Type: Ensemble (ML)
- Description: An extension of bagging using decision trees with added randomness.
- Pros:
  - High accuracy and robustness.
  - Can handle high-dimensional data (e.g., TF-IDF features).
  - Feature importance analysis.
- Cons:
  - Black-box model.
  - Less effective without meaningful feature engineering for text.
- Use in Depression Detection:
  - Often used with extracted features from text (e.g., LIWC, n-grams).
  - Performs well with moderate feature sets.

7.3. Linear SVC (Support Vector Classification)

- Type: Classical ML
- Description: A linear classifier based on support vector machines.
- Pros:
  - Excellent for high-dimensional text data.
  - Efficient and robust with sparse features (e.g., TF-IDF).
- Cons:
  - Sensitive to parameter tuning (e.g., regularization).
  - Not probabilistic (though probabilities can be estimated).
- Use in Depression Detection:
  - Strong baseline model for text classification.
  - Often used in traditional NLP pipelines.

7.4. Logistic Regression

- **Type**: Classical ML
- **Description**: Statistical model predicting probability of a binary class.
- **Pros**:

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- Simple, interpretable.
- Works well with TF-IDF features.

- **Cons**:
  - Struggles with non-linearly separable data.
- **Use in Depression Detection**:
  - Effective with engineered text features.
  - Can serve as a lightweight benchmark.

7.5. Naive Bayes

- **Type**: Probabilistic ML
- **Description**: Assumes feature independence; often used in text classification.
- **Pros**:
  - Fast and scalable.
  - Performs surprisingly well for short texts.
- **Cons**:
  - Strong independence assumptions may not hold.
  - Doesn't model word context well.
- **Use in Depression Detection**:
  - A solid baseline for text classification tasks.
  - Best used with bag-of-words/TF-IDF features.

Results:

- Bagging performed the best overall, achieving the highest accuracy and recall.
- Random Forest closely followed, showing strong balanced performance across all metrics.
- Logistic Regression had excellent recall but slightly lower precision.
- Linear SVC performed moderately well but slightly below the ensemble methods.
- Naive Bayes had the lowest performance among all models.

Overall, ensemble methods (Bagging and Random Forest) outperformed individual classifiers, making them more effective for depression detection in textual data.

Model	Precision	Recall	F1-Score	Accuracy
Random Forest	0.7963	0.8329	0.8894	0.8243
Bagging	0.8081	0.8315	0.8239	0.8162
Linear SVC	0.8609	0.8524	0.8564	0.8504
Logistic Regression	0.9275	0.9195	0.8965	0.9158
Naive Bayes	0.9243	0.9198	0.9220	0.9283

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
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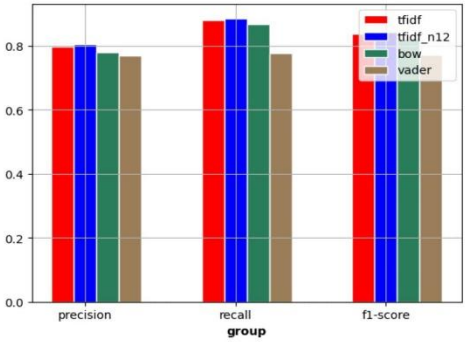

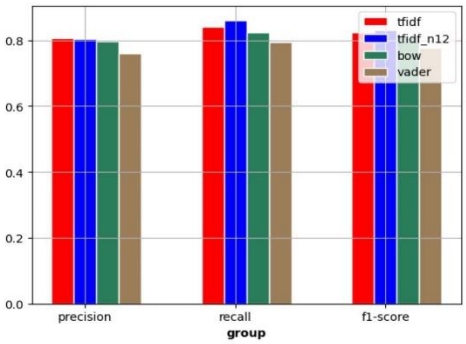

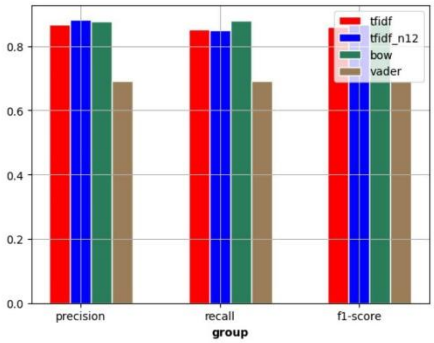

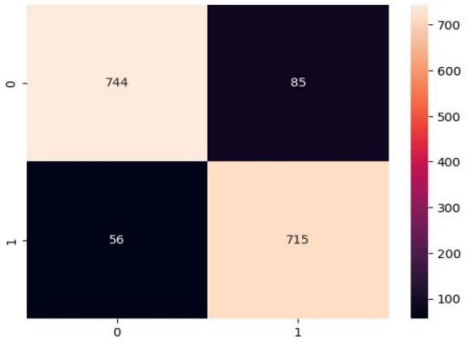

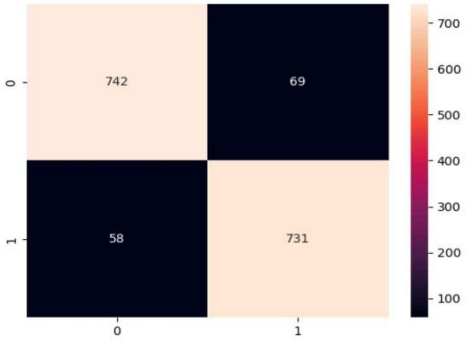

Conclusion:

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This study evaluated the effectiveness of various machine learning models—Random Forest, Bagging, Linear SVC, Logistic Regression, and Naive Bayes—for detecting depression from textual data. The findings demonstrate that ensemble methods, particularly Bagging and Random Forest, outperformed individual classifiers in terms of accuracy, precision, recall, and F1-score. Logistic Regression showed strong recall but lower precision, while Naive Bayes consistently achieved the lowest performance across metrics.

These results highlight the value of ensemble learning approaches in improving the reliability and robustness of depression detection models using text-based features. By leveraging such models, it is possible to develop more accurate and scalable tools for early identification of depression through digital communication platforms.

Future work could explore incorporating additional linguistic features, applying more advanced natural language processing techniques, or validating the models across diverse datasets to further enhance performance and generalizability.

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