ANU COLLEGE OF ENGINEERING AND TECHNOLOGY

Computer science and engineering

DEPRESSION DETECTION USING MACHINE LEARNING MODELSAND DEEP LEARNING

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contents

ABSTRACT:

Objective: This study aims to detect signs of depression in text data using a combination of traditional machine learning models (e.g., LinearSVC , Random Forest, logistic regression ,naïve bayes ,Bagging) and advanced deep learning techniques.

Approach: Traditional models are trained using TF-IDF and Bag-of-Words, while a fine-tuned **BERT** model is used to capture deeper contextual meaning for binary text classification.

Results: Experimental evaluations show that although machine learning models perform reasonably well, the BERT-based deep learning approach significantly outperforms them in terms of accuracy and generalization.

Implications: The findings highlight the effectiveness of combining classic and modern AI methods for early detection of depression, which can support digital mental health interventions.

Keywords: machine learning, deep learning ,BERT , random forest, logistic regression , naïve bayes, SVC , bagging

INTRODUCTION:

Key Points on Depression Detection Using Technology:

1.Challenges in Traditional Depression Diagnosis

Depression is a major global health concern, affecting over 280 million people and contributing to emotional distress, disability, and suicide.

Early detection of depressive symptoms is essential for timely intervention and improved mental health outcomes.

2.Text Data for Depression Detection

1.Sources include social media platforms, online forums, and mental health questionnaires.

2.Language use may reflect depressive tendencies, with negative sentiment, pessimistic word choices, and decreased communication frequency being common indicators.

3. Machine learning methods:

This study uses traditional ML algorithms—**LinearSVC , Random Forest, logistic regression , naïve bayes**, and **Bagging on the suicide.csv** dataset using TF-IDF and bag of words for feature extraction .

Deep Learning Approach with BERT:
We also apply **BERT**, a transformer-based deep learning model, to capture deeper semantic and contextual patterns in text for better classification accuracy.

Research Objective:
The aim is to compare ML and DL approaches in detecting depression-related text, contributing to the development of automated systems for mental health monitoring.

LITERATURE REVIEW:

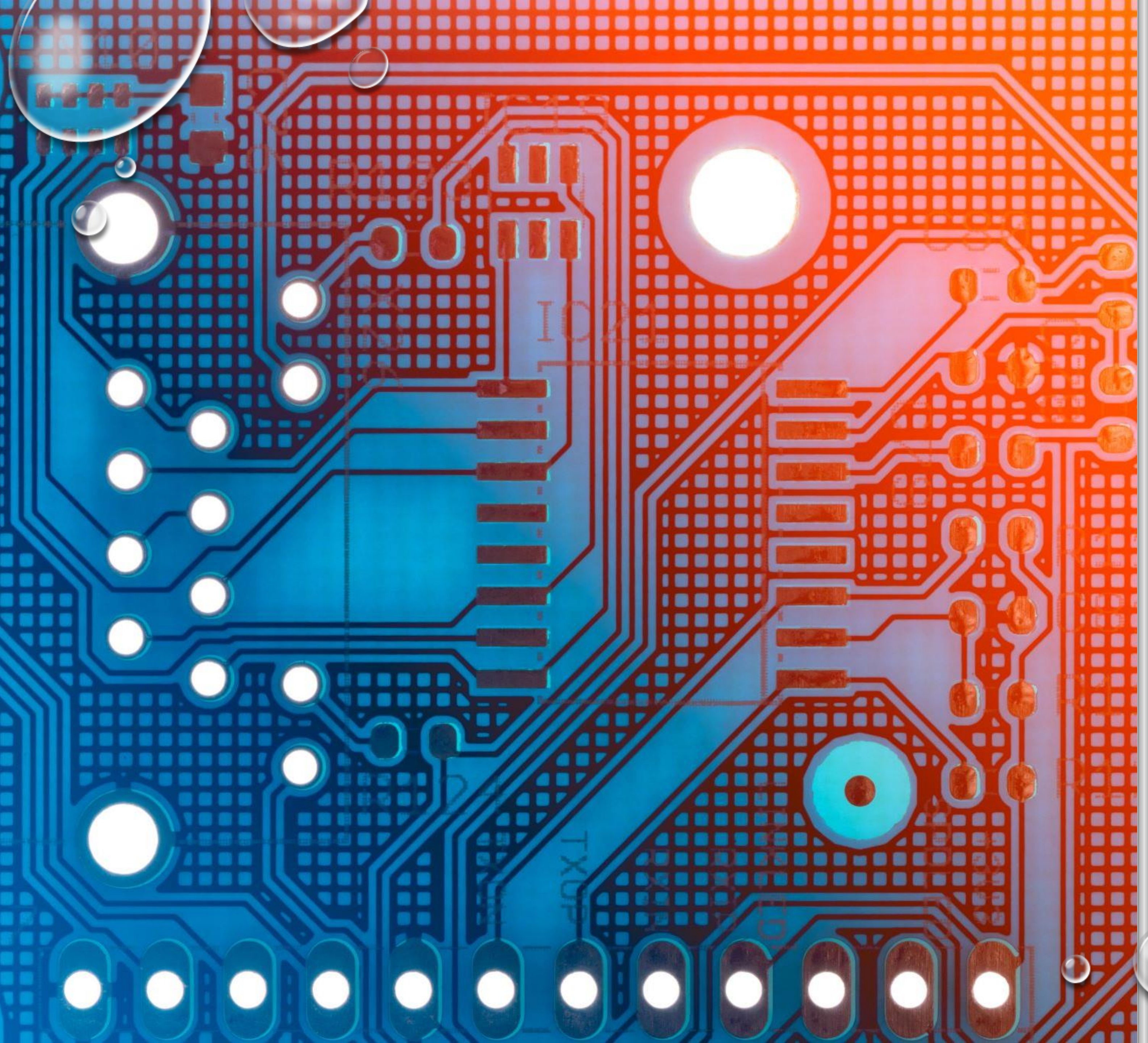
Author(s) & Year	Technique(s) Used	Dataset / Source	Key Findings
Yates et al. (2017)	SVM, Logistic Regression, TF-IDF	Reddit Mental Health Posts	Achieved high accuracy in depression detection using traditional ML models.
Coppersmith et al. (2015)	Random Forest, Bag-of-Words	Twitter Mental Health Corpus	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 (BooksCorpus, 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.
Present Study (2025)	LinearSVC, RF, Bagging, BERT	suicide.csv (Reddit-like Posts)	Combines traditional and deep learning models; BERT shows superior accuracy.

Problem statement

develop a system that accurately identifies individuals at risk of depression based on features extracted from patient data.

- Detect depression based on text data such as survey responses or social media posts.
- predict whether a person is **depressed** or **not depressed** based on text analysis.
- Use a combination of **TF-IDF, Linear SVC , Random Forest , logistic regression , naives bayes** and **Bagging Method** to improve accuracy and also use DL techniques like **bert**

The problem formulation involves defining the problem statement, identifying the target population, and specifying the input and output of the system. This helps clarify the goals of the project and guide the selection of machine learning algorithms and evaluation metrics.



- SYSTEM REQUIREMENT SPECIFICATIONS :

HARDWARE REQUIREMENTS :
1)OPERATING SYSTEM : WINDOWS (OR) MAC OS
2)PROCESSOR : I3 AND ABOVE
3)RAM : 4GB AND ABOVE
4)HARD DISK : 50 GB
SOFTWARE REQUIREMENTS :
1)VISUAL STUDIO COMMUNITY VERSION OR ANACONDA NAVIGATOR

- 2)PYTHON IDLE (PYTHON 3.7)

LANGUAGE – PYTHON

Existing predictive models suffer from significant limitations:

Data Imbalance: Imbalanced datasets can lead to biased predictions, reducing the accuracy of models like SVC, Random Forest , logistic regression and Bagging.

Multimodal Integration Challenges: Difficulty in effectively combining text data (sentiment analysis) for holistic detection.

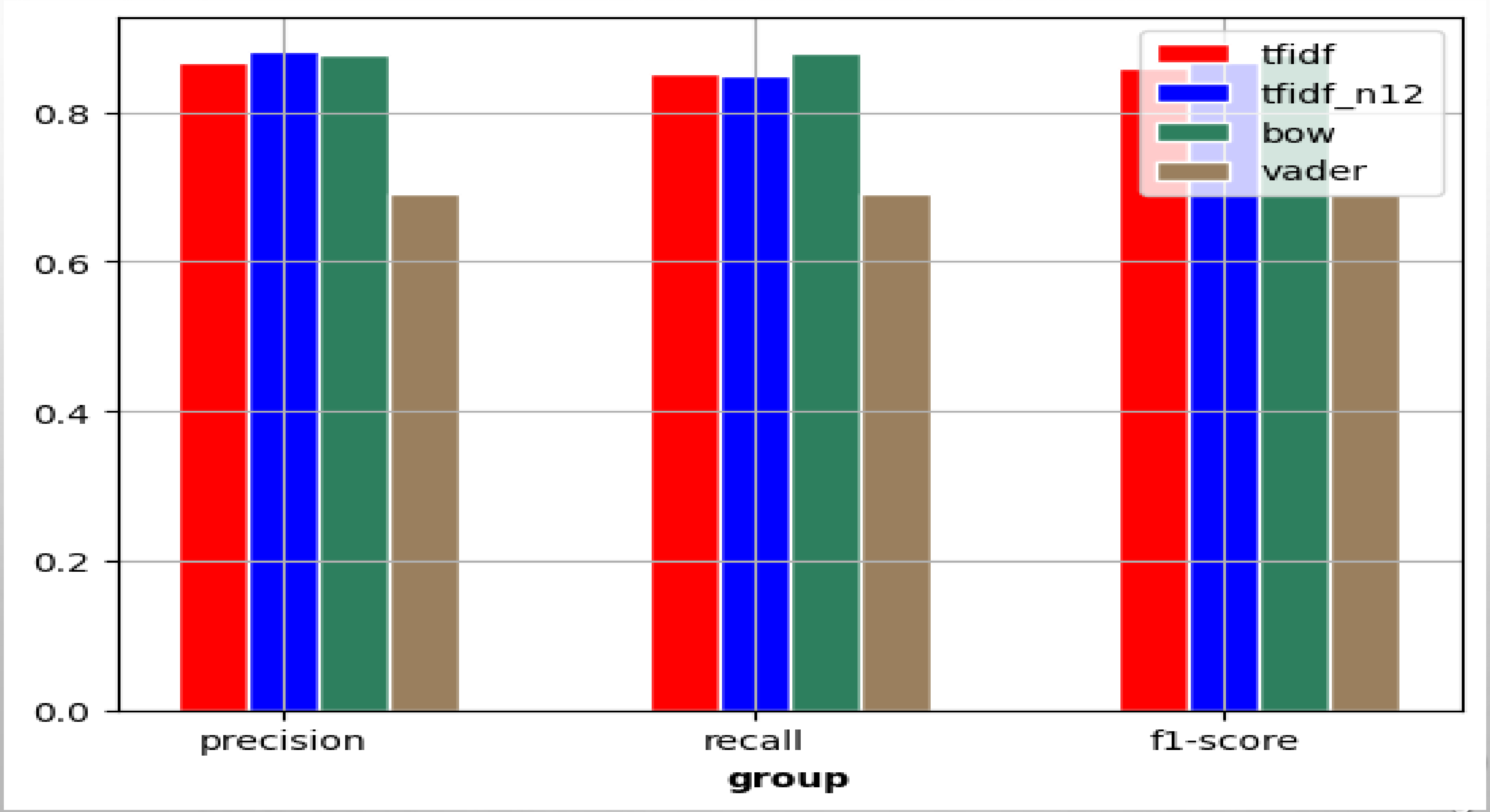
Scalability and Interpretability Issues: These models may face challenges in scaling to larger datasets and are often less interpretable for understanding underlying patterns.

Noise and Context Dependency: Noisy, unstructured, and context-dependent data (e.g., text) can lower model accuracy.

Privacy and Ethical Concerns: Handling sensitive user data (mental health information) raises privacy and ethical issues that need careful consideration

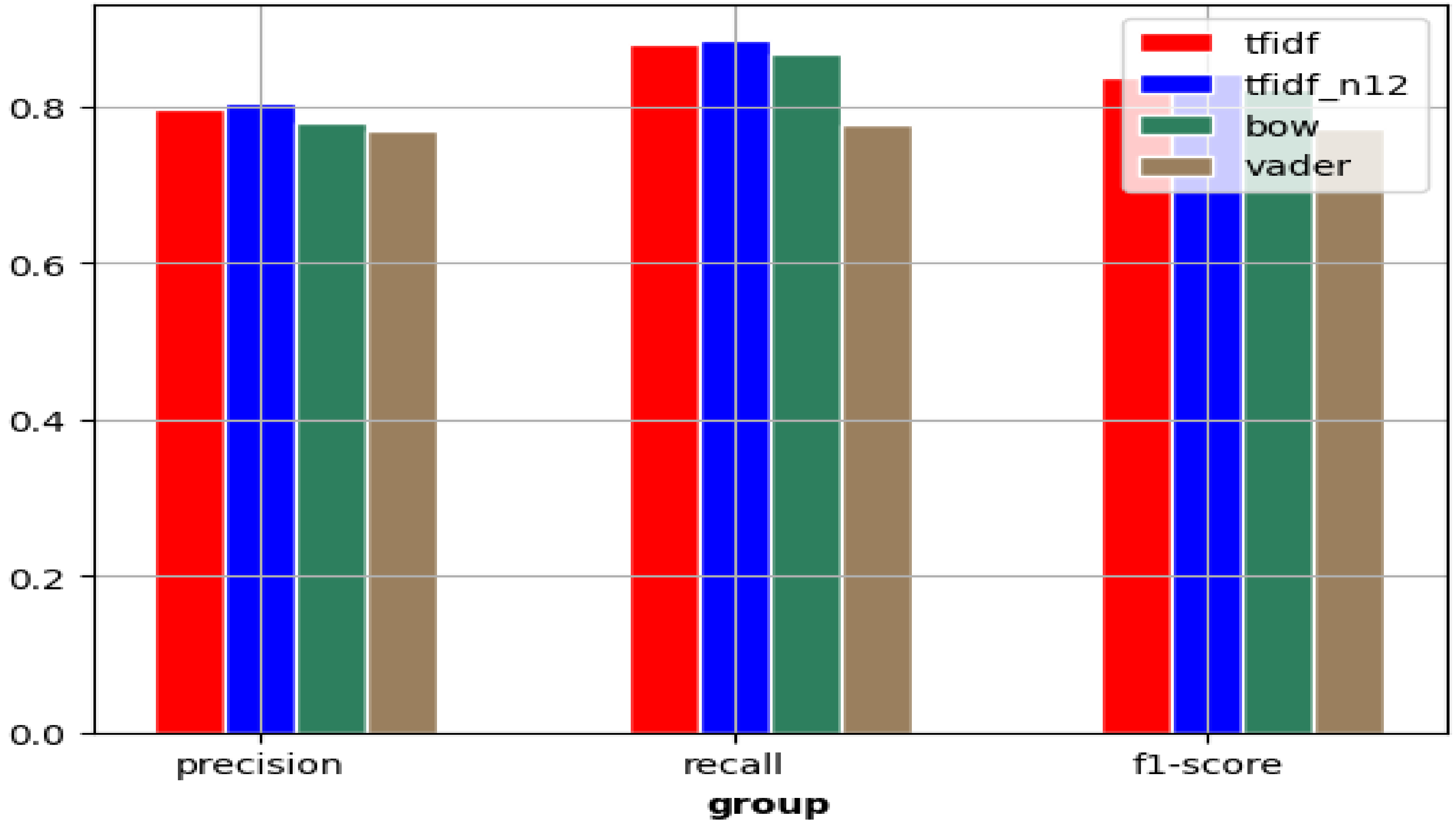
Observations

LINEAR SVC PERFORMANCE

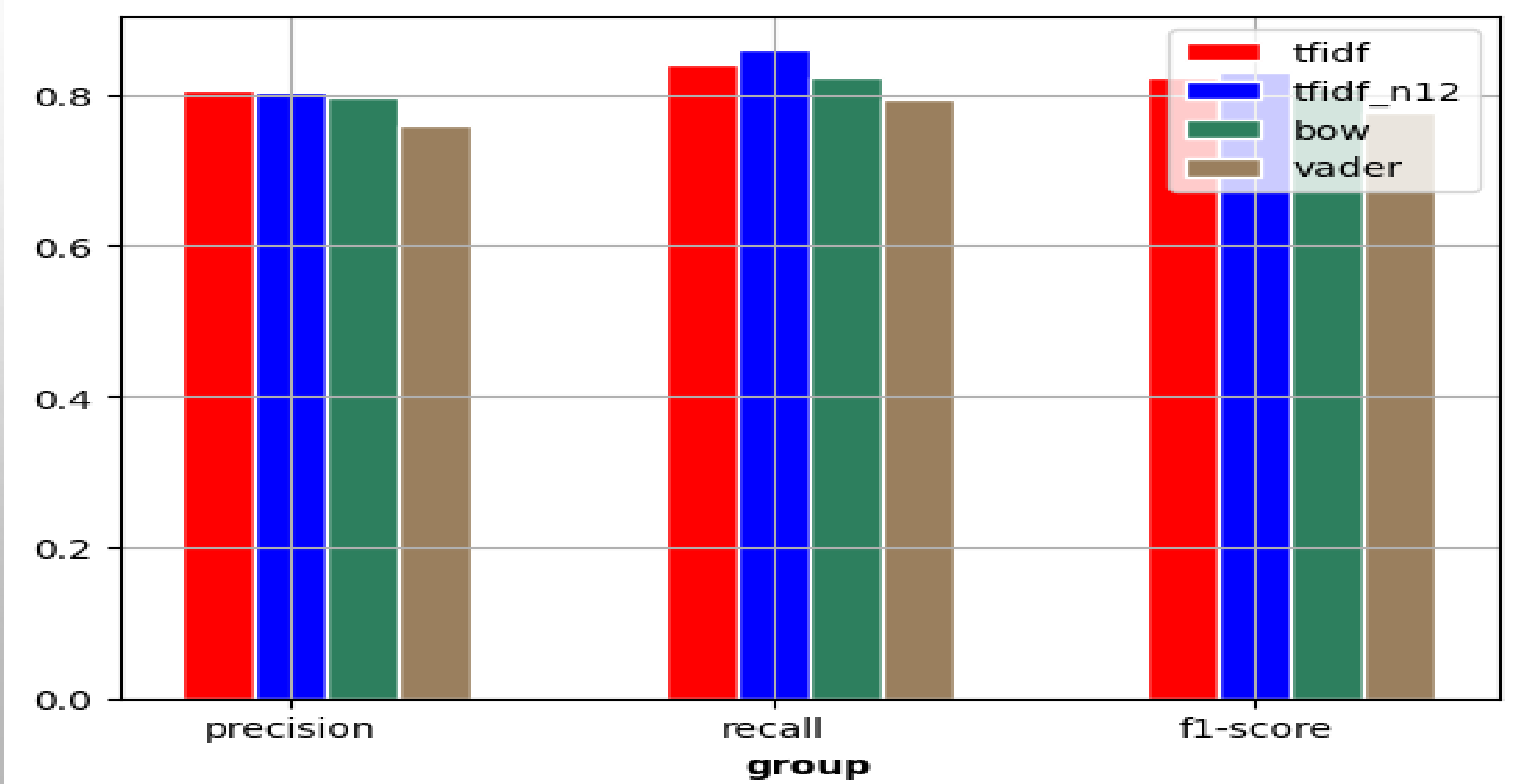


Observations

RANDOM FOREST PERFORMANCE

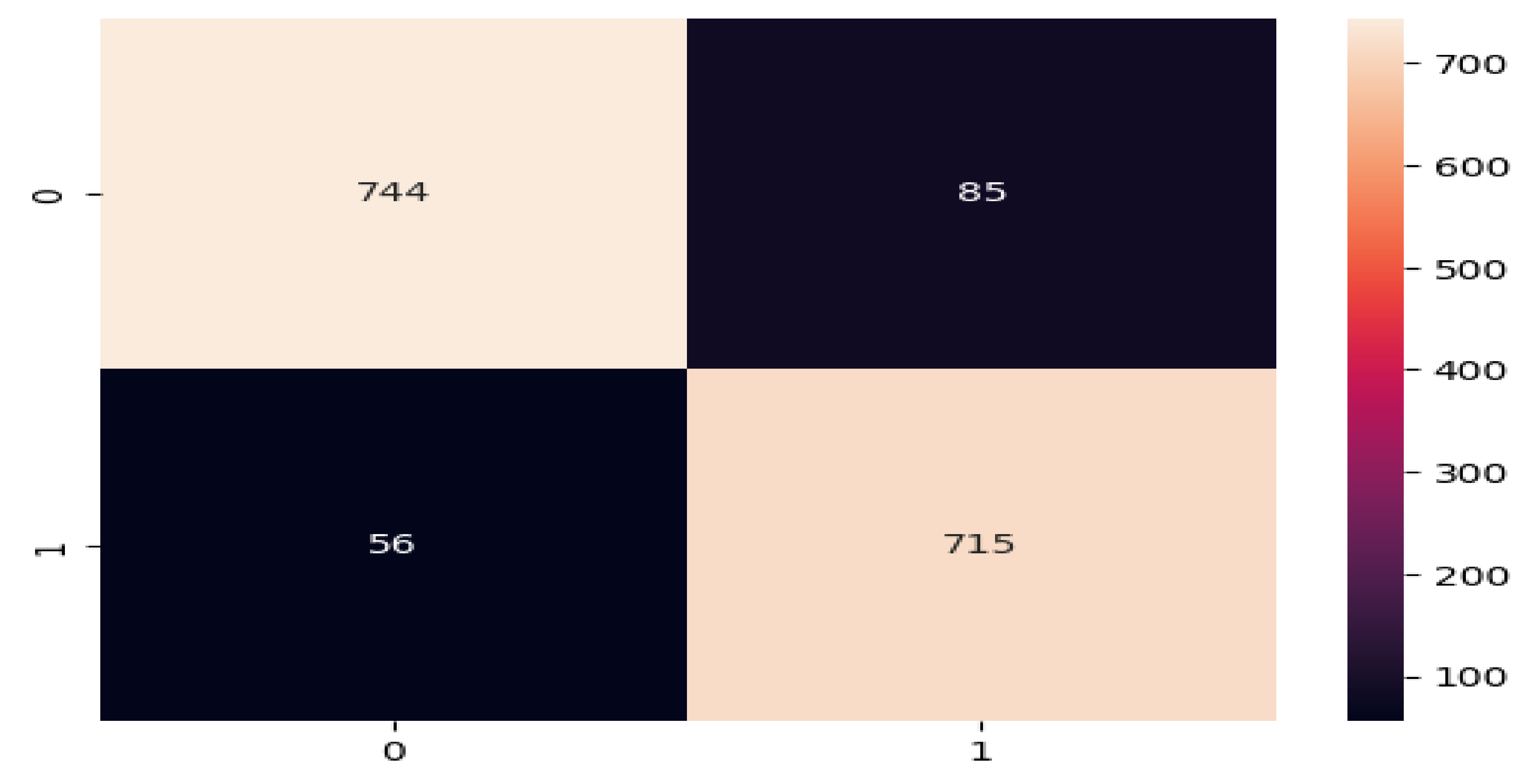


BAGGING PERFORMANCE



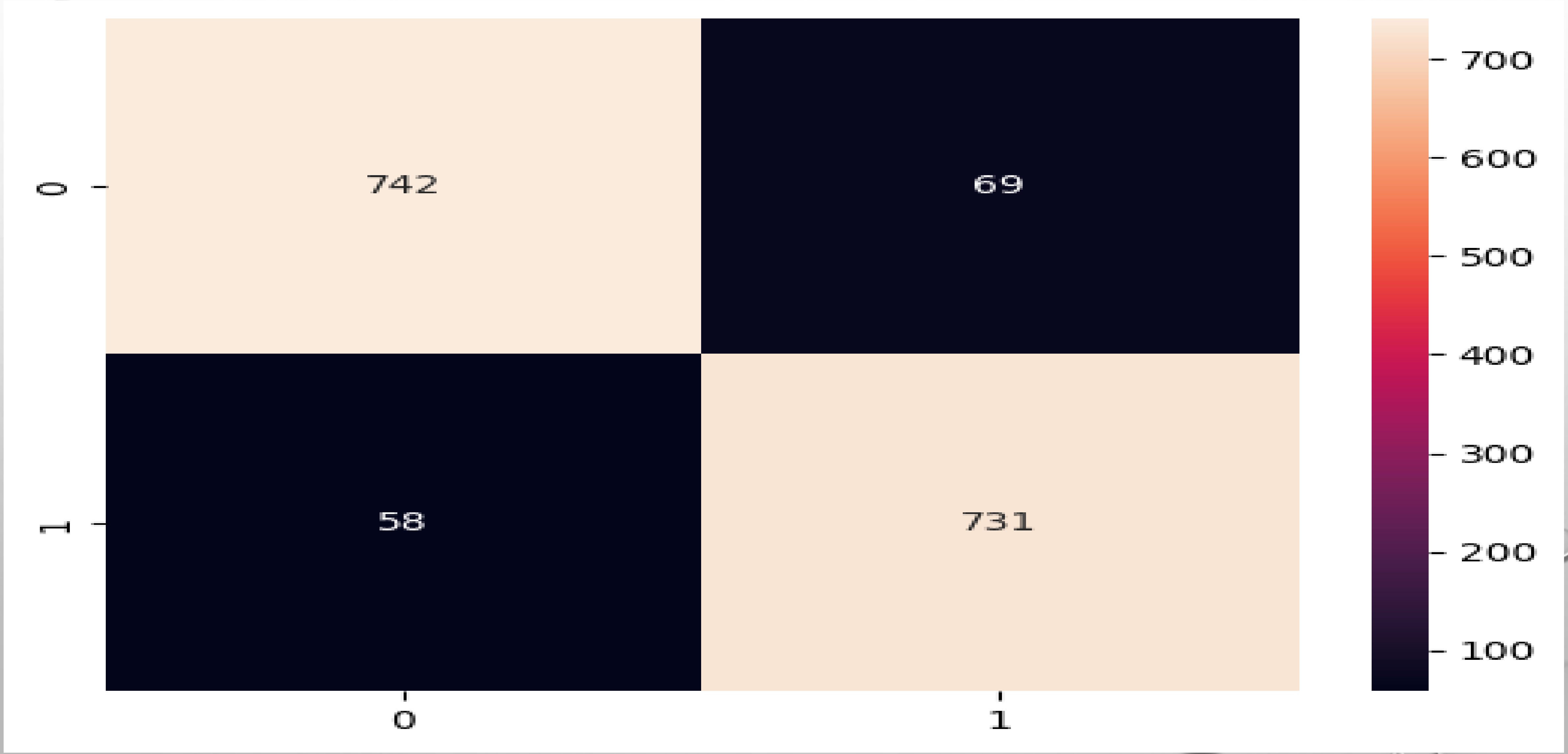
Observations

LOGISTIC REGRESSION PERFORMANCE



Observations

NAÏVE BAYES PERFORMANCE



Proposed learning:

1. Utilize Traditional Machine Learning Techniques

•Apply classical machine learning models such as **Linear Support Vector Classifier (LinearSVC) , Random Forest, logistic regression , naïve bayes** and **Bagging.**

•Use **TF-IDF** and **Bag-of-Words** to transform the text into feature vectors.

•Evaluate performance based on accuracy, precision, recall, and F1-score.

2.Implement Advanced Deep Learning with BERT

•Fine-tune the pre-trained **BERT (Bidirectional Encoder Representations from Transformers)** model for binary classification (suicidal vs. non-suicidal posts).

•Leverage BERT's ability to understand deep semantic and contextual meaning in textual data.

3. Comparative Analysis

•Compare the performance of traditional machine learning models with the deep learning BERT model.

•Analyze metrics such as validation accuracy, classification report (precision, recall, F1-score) for both approaches.

4. Address Class Imbalance and Overfitting

•Implement techniques like stratified sampling during train-test split, and use dropout or regularization (in BERT) to prevent overfitting.

Propose a complete depression detection system that could be extended for real-time monitoring applications using social media data or online text entries.

METHODOLOGY:

1. Data Collection and Preprocessing

•The **Suicide Detection Dataset** (suicide.csv) containing text posts labeled as "suicidal" or "non-suicidal" was used.

•Basic preprocessing steps include:

- Removal of missing/null values.
- Label Encoding: "suicide" mapped to 1, "non-suicide" mapped to 0.
- Text cleaning (optional): removing special characters, lowercasing, etc.

2. Feature Engineering for Machine Learning Models

•Text data was transformed into numerical form using:

- **TF-IDF (Term Frequency-Inverse Document Frequency)**.
- **Bag-of-Words (BoW)** representations.

•These features were used as input for classical ML models.

3. Traditional Machine Learning Models

- Several machine learning classifiers were trained and evaluated:
    - **Linear Support Vector Classifier (LinearSVC).**
    - **Random Forest Classifier.**
    - **Logistic regression**
    - **Naives bayes**
    - **Bagging Classifier.**
- Hyperparameters were fine-tuned using cross-validation.
- Performance was measured using **Accuracy**, **Precision, Recall,** and **F1-Score**.

4. Deep Learning with BERT

- Pre-trained **BERT (bert-base-uncased)** model was fine-tuned for binary classification.
- Steps involved:
    - Tokenizing the text using **BertTokenizer** .
    - Creating custom **PyTorch Datasets** and **DataLoaders** for training and validation.
    - Fine-tuning **BertForSequenceClassification** on the dataset.
    - Using **AdamW optimizer** and **cross-entropy loss.**
    - Model trained for **3 epochs** with batch size **16.**

5. Evaluation Metrics

•Both machine learning and deep learning models were evaluated on:

- **Validation Accuracy**.
- **Classification Report** (Precision, Recall, F1-Score for each class).

6. Comparative Analysis and Conclusion

•Compared traditional ML models and the BERT model.

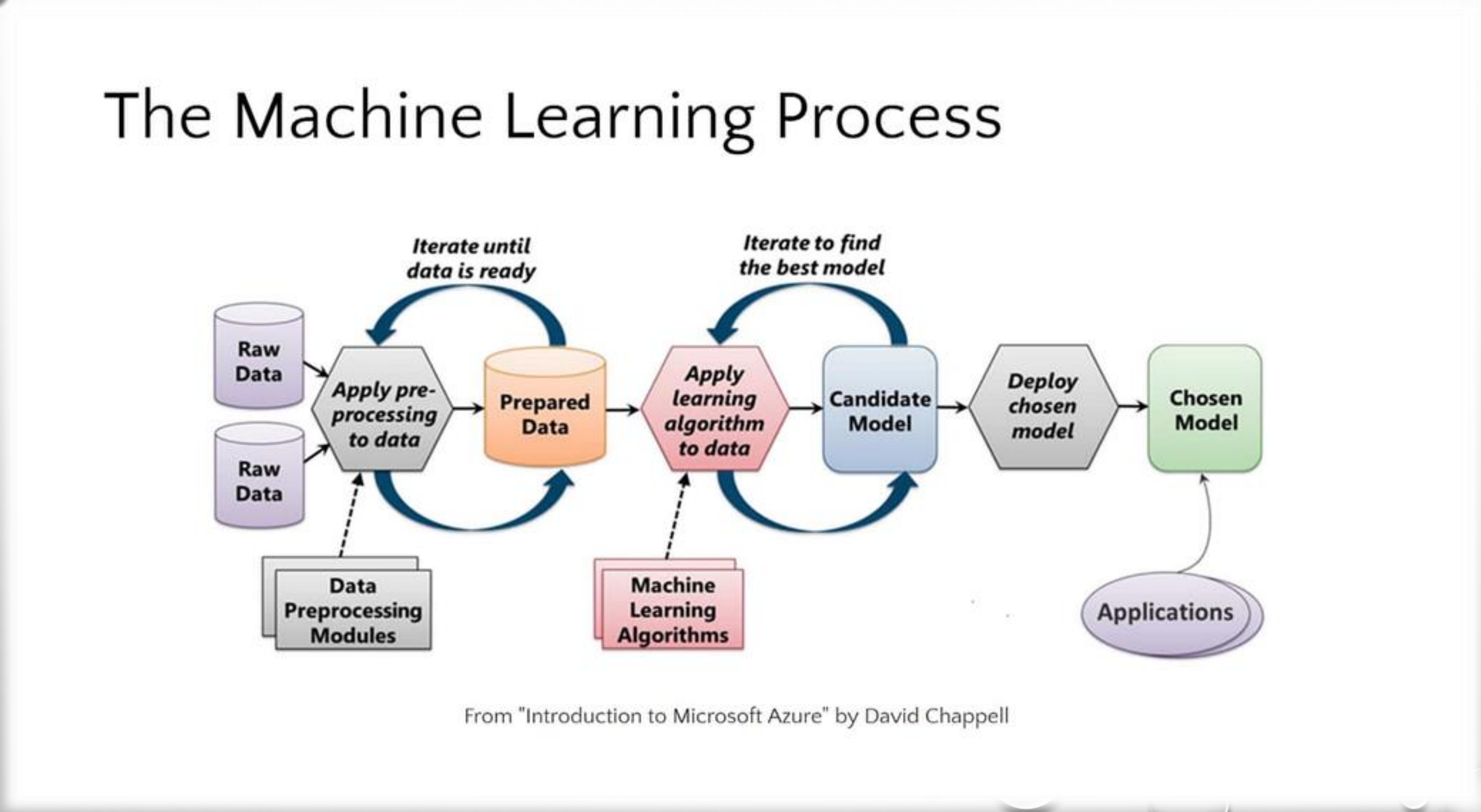
•Highlighted the advantages of deep contextual understanding with BERT.

•Proposed directions for future improvements (e.g., larger datasets, better data augmentation).

Data set overview

Name :suicide_detection dataset.
Total Samples : 232072
Data Types:
2 categorical columns
They are text and label/ class ,class contains two values only depressed or not
Key Column.:
In this key column The textual content from various sources, such as socialmedia posts or forum entries, where individuals discuss their mental health experiences

Dataset preprocessing:



Machine Learning Model Comparison Table:

Model	Accuracy	Precision	Recall	F1-Score	Training Time	Interpretability	Handles Imbalanced Data	Comments
Bagging (Base: DT)	Moderate to High	Good	Good	Good	Moderate	Low (black box)	Yes (with class weighting or sampling)	Reduces variance; good with noisy data
Random Forest	High	High	High	High	Moderate-High	Low	Yes	Ensemble of trees; handles overfitting better
SVC	High (linear data)	Very High	Low (for imbalanced)	Moderate	High (slow on large datasets)	Medium	No (requires tuning or balancing)	Sensitive to feature scaling
Naive Bayes	Moderate	Low	High	Moderate	Fast	High	Poor with correlated features	Best for baseline; assumes independence
Logistic Regression	Moderate	Good	Moderate	Moderate	Fast	High	Needs balancing	Linear decision boundary

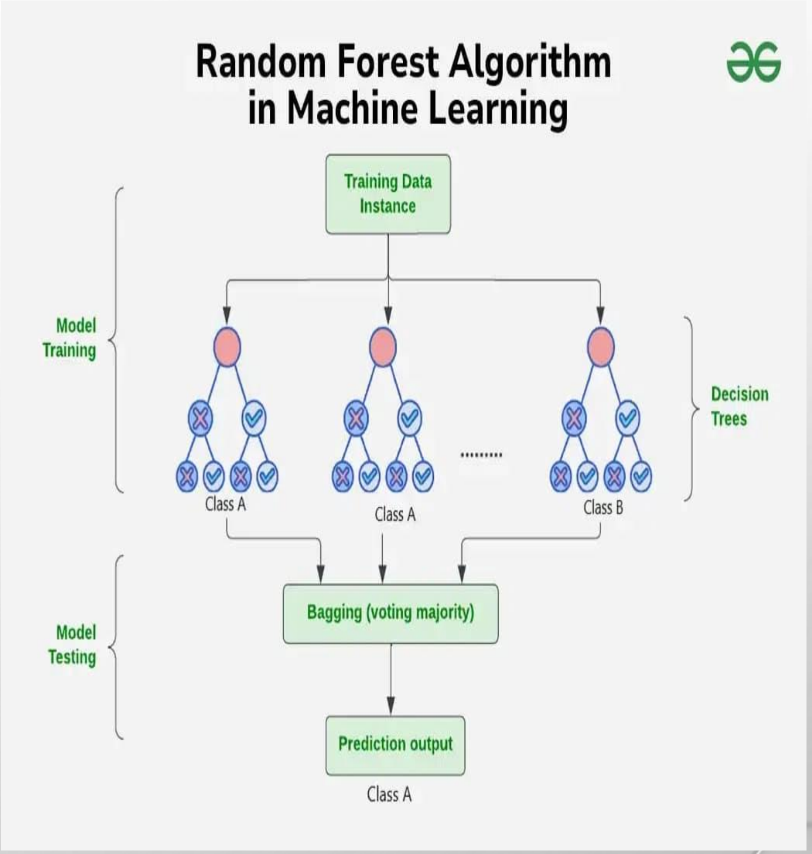
RANDOM FOREST:

MachineLearningApproach:

Random Forest, an ensemble learning algorithm based on decision trees, classifies individuals as depressed or not by leveraging psychological, behavioral, and physiological features. It improves accuracy and reduces overfitting through majority voting across multiple decision trees

DatasetandFeatures:

Depression detection datasets may include diverse data such as sleep patterns, social media activity, speech tone, facial expressions, and clinical questionnaire responses. Proper preprocessing is applied to handle missing values, perform feature selection, and normalize data.



ModelTrainingandEvaluation:

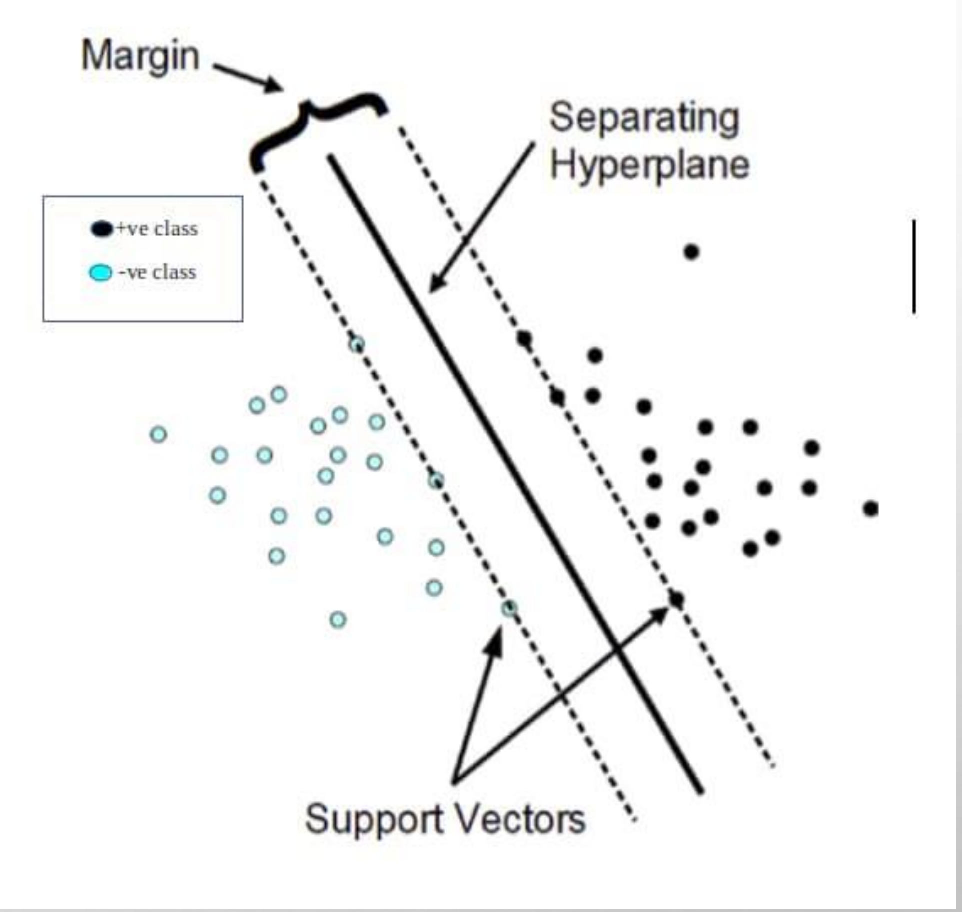
The model is trained on labeled datasets and evaluated using performance metrics like precision, recall, and F1-score to measure accuracy and reliability. Random Forest excels in handling both structured and unstructured data.

HealthcareApplicationandBenefits:

Random Forest ranks feature importance, helping to identify key depression indicators. When integrated into healthcare systems, it supports early diagnosis, timely intervention, and improved mental health outcomes.

Linear svc

- Linear SVC is a machine learning algorithm used for binary classification tasks. It aims to find the optimal hyperplane that best separates data points into two classes, such as "depressed" and "non-depressed.“
- **High-Dimensional Data Handling:**
  It works well with high-dimensional datasets, making it suitable for tasks like text classification, where features (e.g., word frequencies or TF-IDF values) can be numerous.



- **Efficiency and Speed:**
  Linear SVC is computationally efficient, particularly with large datasets, due to its linear kernel, which reduces the complexity compared to non-linear SV

- **Performance Metrics and Evaluation:**
  Its performance is typically measured using metrics like accuracy, precision, recall, and F1-score, ensuring that the model not only classifies accurately but also handles imbalanced data effectively when properly tuned.

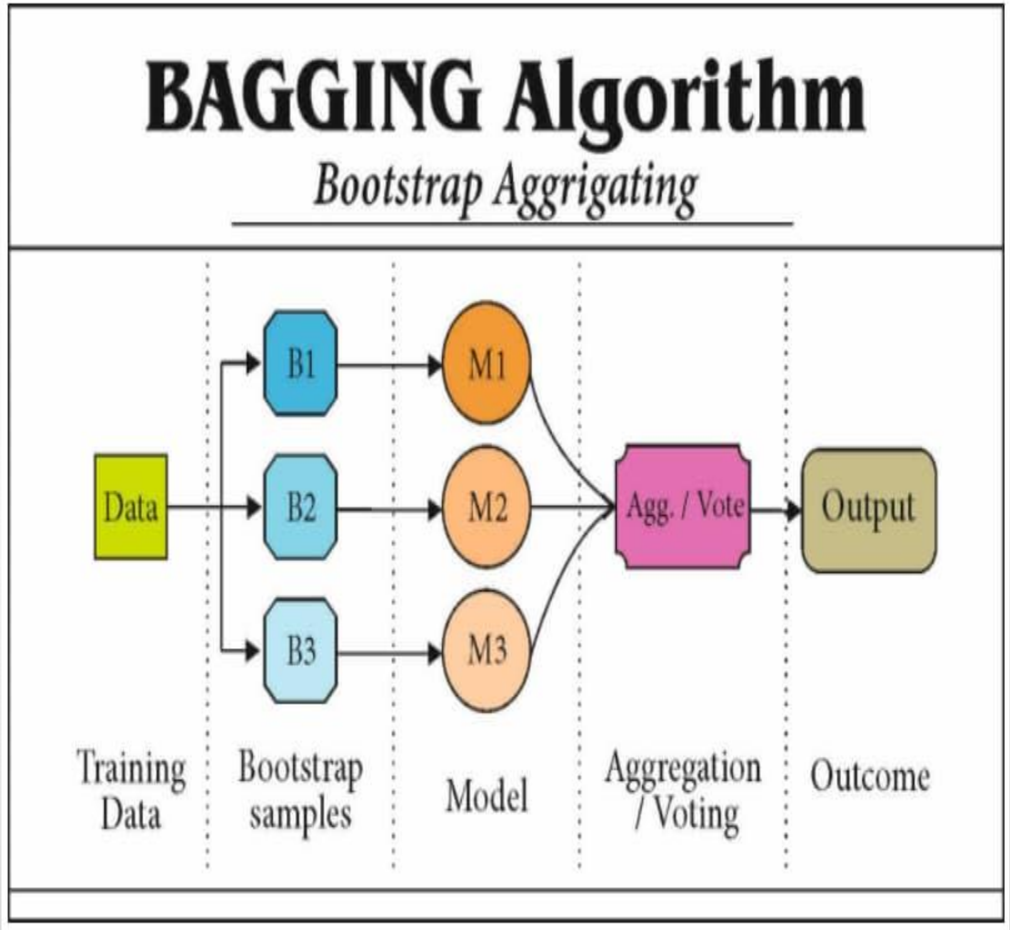
BAGGING:

Bagging is an ensemble learning technique designed to reduce variance and prevent overfitting by creating multiple subsets of the original dataset through bootstrapping (random sampling with replacement). Each subset is used to train a separate model (e.g., decision trees).

After training, the outputs of all individual models are aggregated (e.g., majority voting for classification or averaging for regression) to produce the final, more accurate prediction.

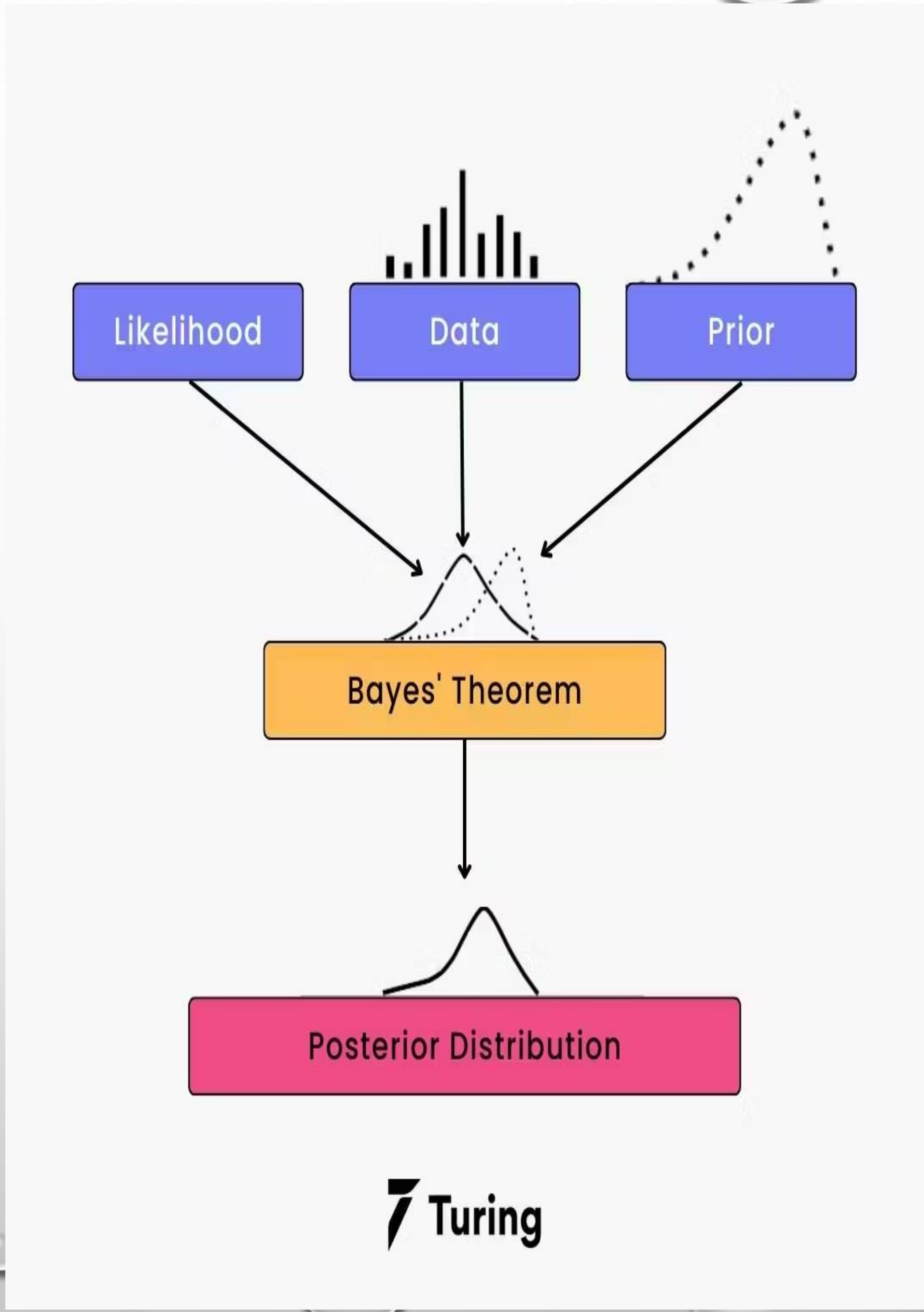
Improved Stability and Accuracy:

Bagging enhances the model's stability and accuracy by minimizing the impact of outliers and noise in the data. Random Forest is a well-known bagging-based algorithm that benefits from diverse decision trees.



Naive Bayes for Depression Detection

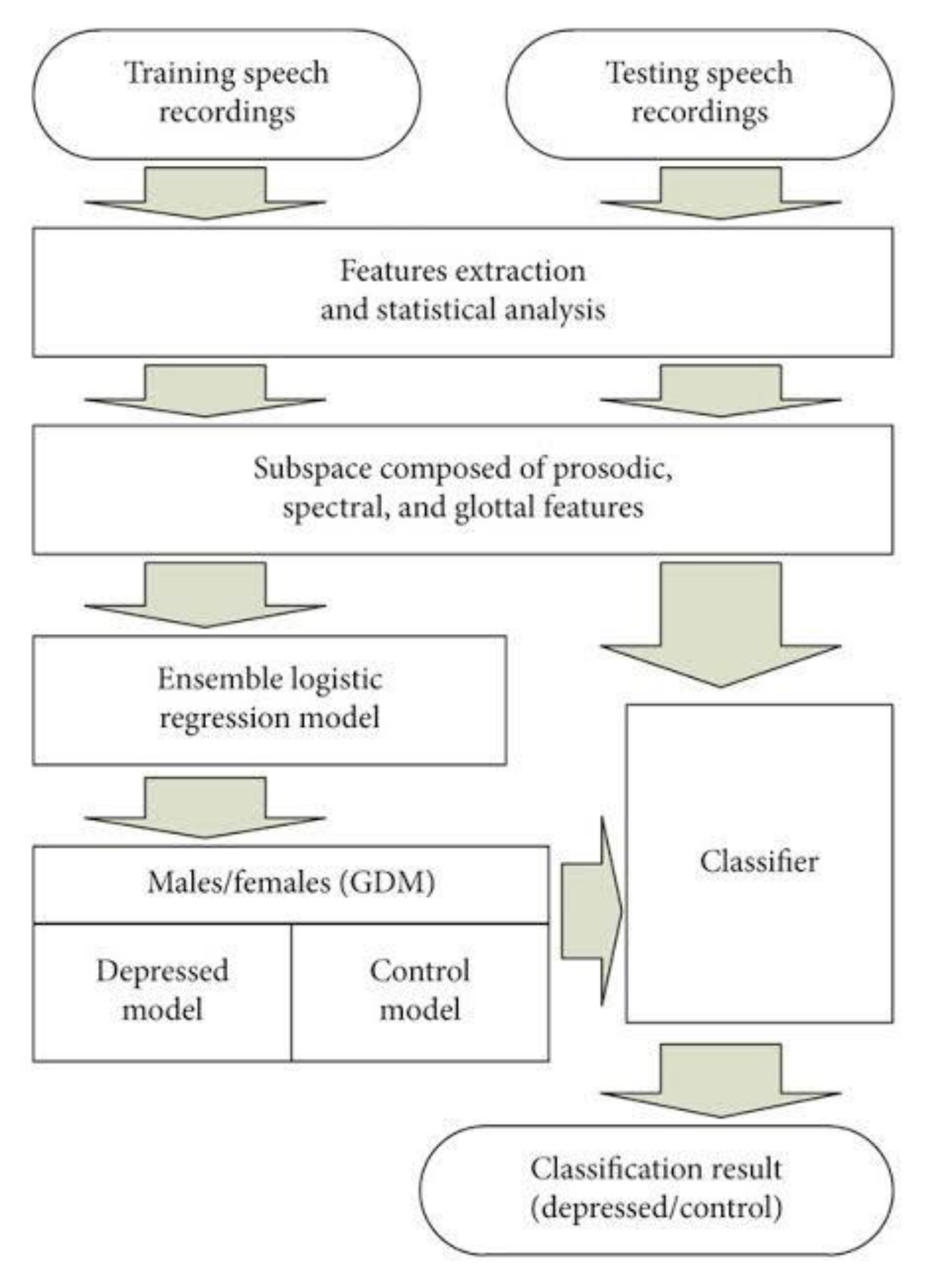
Naive Bayes is a probabilistic machine learning algorithm based on Bayes’ Theorem, commonly used for text classification tasks. In the context of depression detection, it is particularly effective when analyzing textual data such as social media posts, online journals, or survey responses. The model assumes feature independence, which simplifies computations and allows for fast training even on large datasets. Text data is typically transformed into numerical features using methods like TF-IDF or Bag-of-Words before being fed into the classifier.



Despite its simplicity, Naive Bayes performs well in identifying depressive language patterns, especially in datasets where the features (words) strongly indicate emotional states. Its high recall makes it useful for mental health applications where missing a depressed individual could have serious implications. However, its assumption of feature independence and tendency to underperform when features are highly correlated can limit its effectiveness compared to more complex models. Nonetheless, Naive Bayes remains a strong baseline due to its speed, scalability, and effectiveness in early-stage detection systems.

Logistic Regression for Depression Detection:

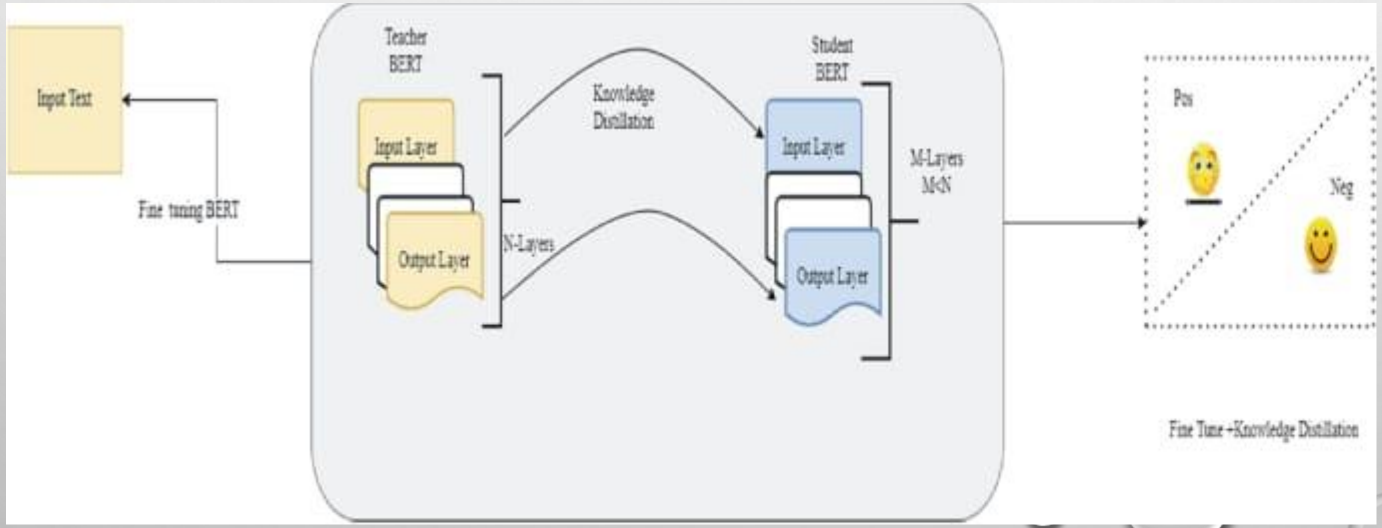
Logistic Regression is a widely used linear classification algorithm that models the probability of a binary outcome, making it a suitable choice for depression detection tasks where the goal is to classify individuals as "depressed" or "not depressed." When applied to textual data such as social media posts or written assessments, Logistic Regression requires the input features to be numerical, typically obtained through techniques like TF-IDF vectorization. One of the key advantages of Logistic Regression is its interpretability;



the model's coefficients provide insight into which words or features contribute most to predicting depression, making it especially valuable in mental health research where transparency is important. It is computationally efficient, handles high-dimensional text data well, and can be enhanced with regularization to avoid overfitting. While it assumes a linear relationship between features and the log-odds of the outcome, which may limit performance in more complex scenarios, Logistic Regression generally provides strong, balanced performance and serves as an excellent baseline for depression detection models.

BERT for Depression Detection:

BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art deep learning model for natural language understanding that has shown exceptional performance in various text classification tasks, including depression detection. Unlike traditional models, BERT captures the contextual meaning of words by considering both their left and right surroundings in a sentence, allowing it to detect subtle linguistic patterns and emotional cues often present in depressive language. For depression detection, BERT can be fine-tuned on labeled text data such as social media posts, therapy transcripts, or self-assessment responses, enabling it to learn domain-specific indicators of mental health conditions. Its deep contextual awareness makes it particularly effective in understanding complex expressions of emotion, sarcasm, or implicit distress that simpler models may miss. While BERT is computationally intensive and requires significant resources for training and deployment, it typically outperforms traditional machine learning models in accuracy and robustness, making it a powerful tool for building reliable, real-time mental health screening systems.



While BERT is computationally intensive and requires significant resources for training and deployment, it typically outperforms traditional machine learning models in accuracy and robustness, making it a powerful tool for building reliable, real-time mental health screening systems.
On the other hand, BERT significantly outperformed traditional models in terms of contextual sensitivity, making it highly suitable for detecting subtle emotional and psychological cues Ultimately, in both approaches in a hybrid framework resulted in a more robust, balanced, and accurate system for depression detection. This project not only demonstrates the The potential of machine learning and deep learning in mental health applications is highlighted, along with the importance of integrating models to harness their strengths.

Future findings:

Furthermore , machine learning has shown great potential for detecting depression using data from **text** . By analyzing text data from social media, blogs, or surveys, machine learning models can identify signs of negative emotions like sadness, loneliness, and hopelessness. Similarly, facial expression recognition helps detect emotions that are often linked to depression, such as sadness or emotional flatness.

CONCLUSION

In this project, a comprehensive approach was taken to detect depression using both traditional machine learning techniques—such as Logistic Regression, Naïve Bayes, Random Forest, Bagging, and Support Vector Classifier—and advanced deep learning models like BERT. Each method offered unique strengths: traditional models provided speed, simplicity, and interpretability, while BERT brought deep contextual understanding and high accuracy through its transformer-based architecture. The comparative analysis showed that although traditional models are effective for baseline classification, they often lack the depth needed to fully interpret nuanced language patterns associated with depression.

THANK YOU