Bangabandhu Sheikh Mujibur Rahman
Digital University

Thesis Defense On

Breaking the Misinformation Barrier: A Comparative Study of Machine Learning and Deep Learning Approaches to Fake News Detection

Presented By:

Student Name	Student ID
Md. Tarif Mahmud	1902007
Mst. Hanium Maria	1902012

Supervised By:

Rubel Sheikh

Lecturer, Educational Technology and Engineering

BDU

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INTRODUCTION

- The spread of **Fake news** is a big problem. It affects people's views and trust. Traditional ways of detecting fake news aren't working anymore, so we need to use modern technology.
- The study evaluates various **Machine Learning Models** (Random Forest, Logistic Regression, Naive Bayes, Passive Aggressive Classifier) to identify the most accurate approach.
- **LSTM** with **Word2Vec** and fine-tuned **BERT** were used for better context understanding.
- Explainable AI techniques like **LIME** are used to interpret and increase the transparency of model predictions.

Objectives

- To explore the challenges of detecting fake news
- To assess the performance of ML and DL models in fake news detection on public dataset
- To explore the integration of multiple approaches for fake news detection
- To improve transparency in fake news detection models using Explainable AI (XAI)

Literature Review

Author	Dataset Source & Size	Applied Model	Highest Accuracy	Limitations
G. Singh et al.[2023]	ISOT, Kaggle & 25,512	SVM, Naive Bayes, RF,LR	97% (SVM)	No XAI use, Does not include models BERT or LSTM
R. Kozik et al.[2024]	Covid19 & 11,000	BERT-based model	92.6% (BERT)	focus on SHAP only, lacks model robustness analysis
M. Lupei et al.[2024]	LIAR & 10,270	SVC, SVR, LR	79.3%(LR)	Small datasets, no advanced models (e.g., BERT, LSTM)
K. Johith Kumar et al.[2024]	Kaggle & 20,800	LR, SVM, Naïve Bayes, DT, CNN, LSTM	95%(CNN & LR)	no transformers like BERT & XAI Use
N. Tabassoum et al. [2024]	NM & 6,940	SBERT, RF, LR, KNN	91.48%(RF)	Small dataset size,No XAI Use

Contribution

Integrated Approach
We combine ML, DL, and XAI techniques to improve fake news detection.

Data Preprocessing
We cleaned the data by removing unnecessary elements like HTML tags and stop words, making it ready for analysis

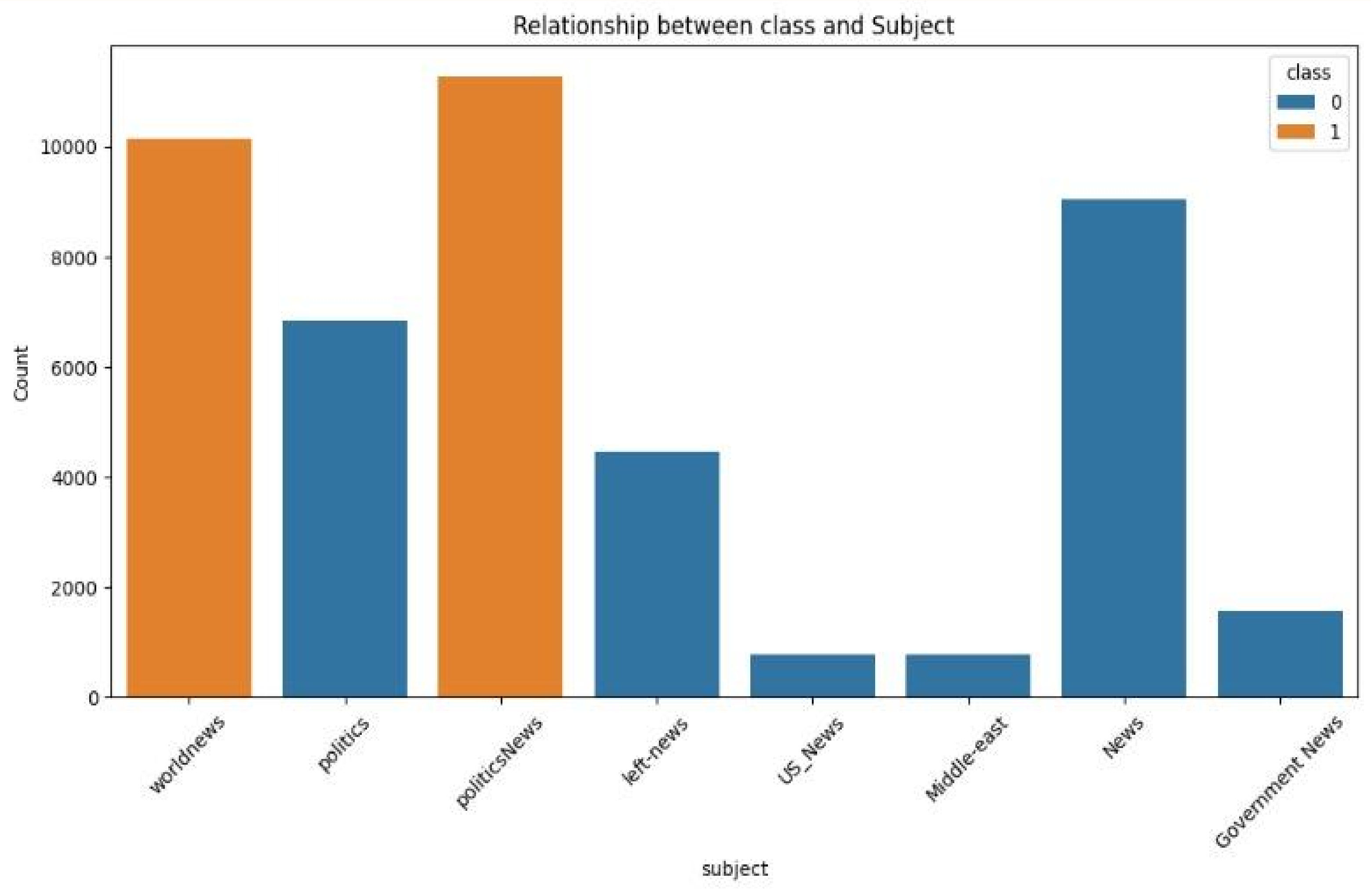
Model Application
We applied various models like Random Forest, Logistic Regression, LSTM, and BERT to detect fake news

Improved Transparency
Using LIME, we made the model's predictions more understandable by showing which words influenced the results.

Dataset Description

- Our dataset is taken from a **Kaggle** dataset of **44,916** news articles.
- These articles are divided into two categories: **23,497** labeled as fake news and **21,419** labeled as real news.
- The dataset contains **five** main features for each article, namely title, text, subject, level and date.

Dataset Description(Contd.)



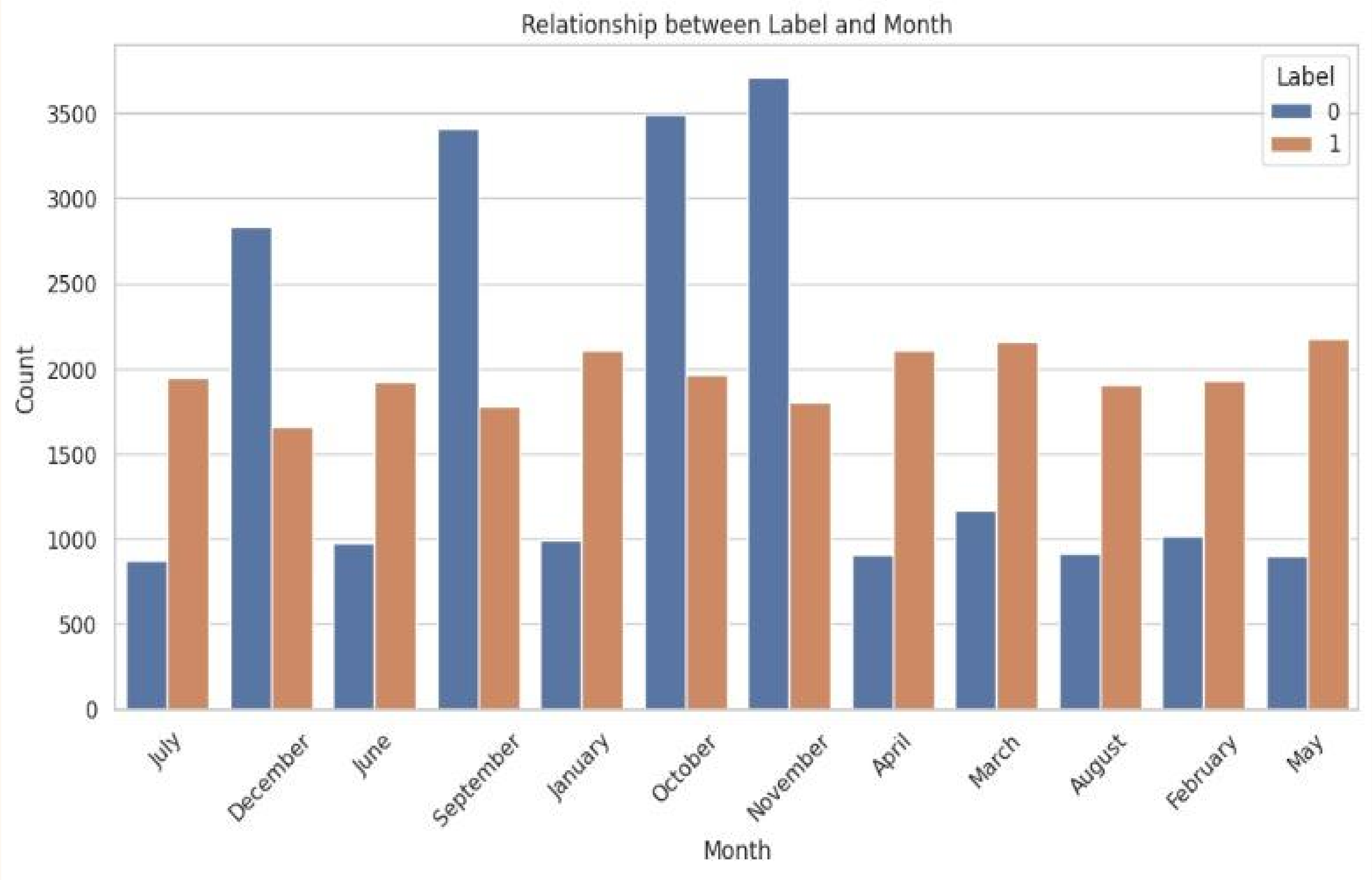
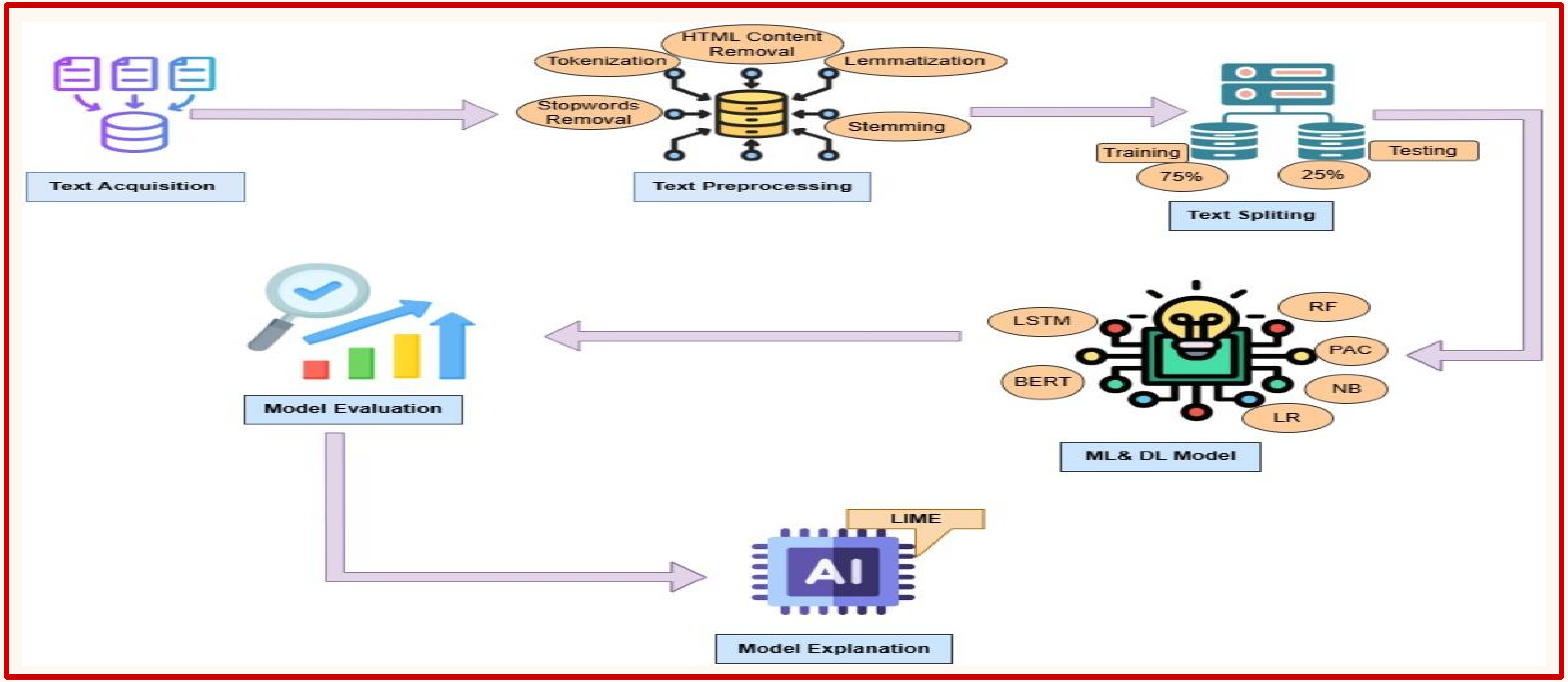


Fig: Relationship between Class and Subject

Fig: Relationship between Label and Month

Dataset Description(Contd.)

Methodology



Working Procedure to Predict Fake news

Confusion Matrix

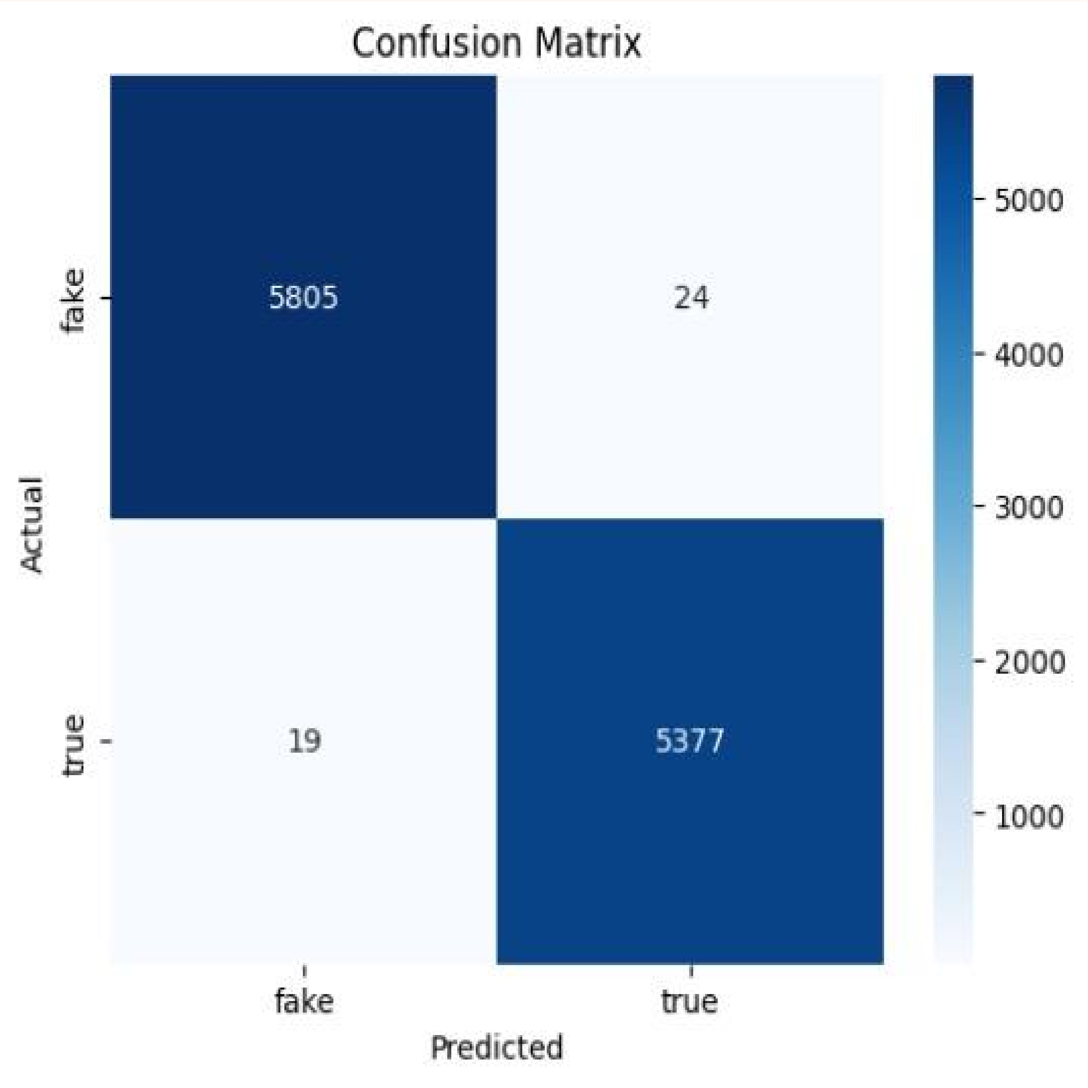


Figure: Confusion Matrix of Passive Aggressive Classifier

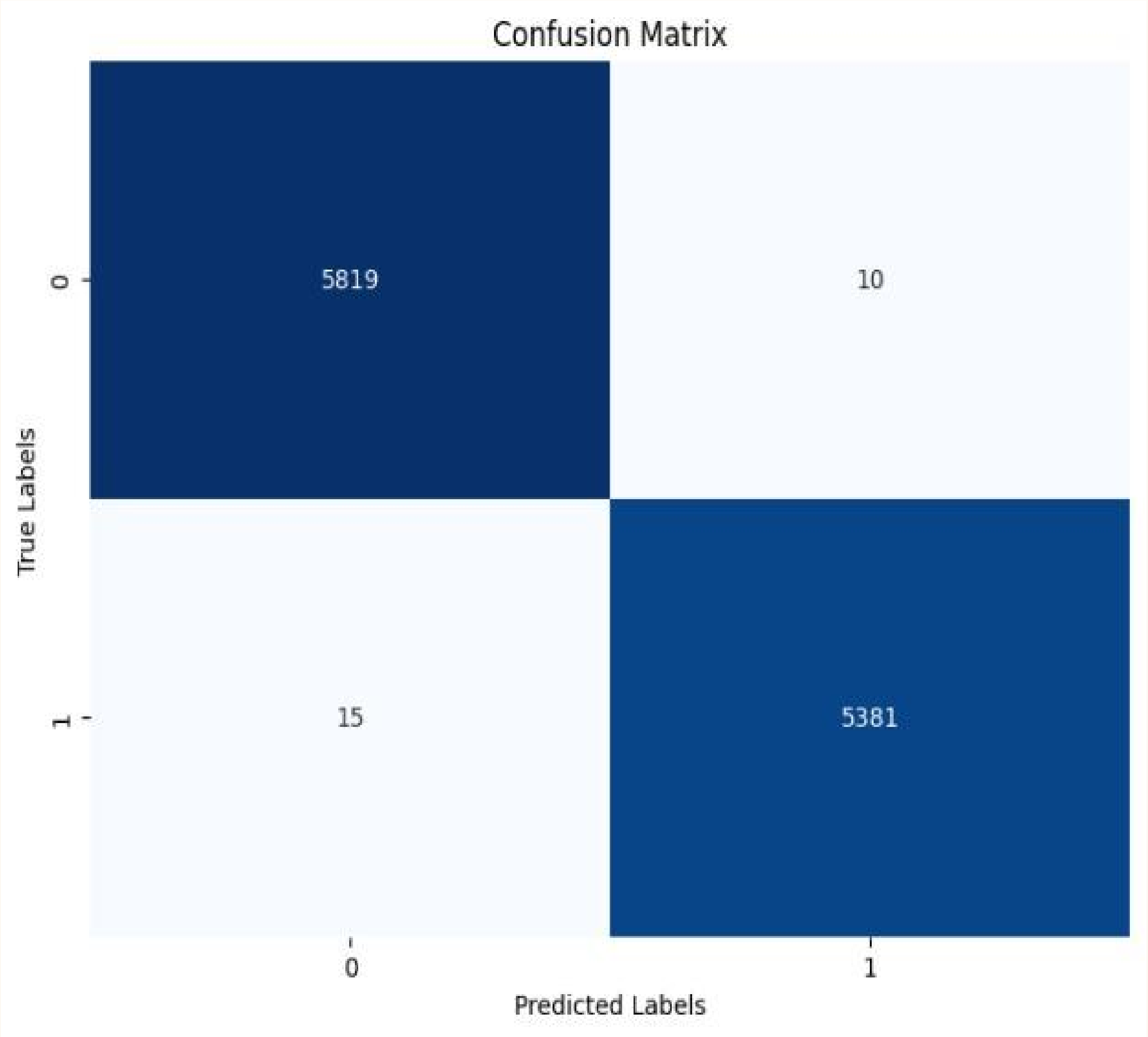


Figure: Confusion Matrix of Random Forest

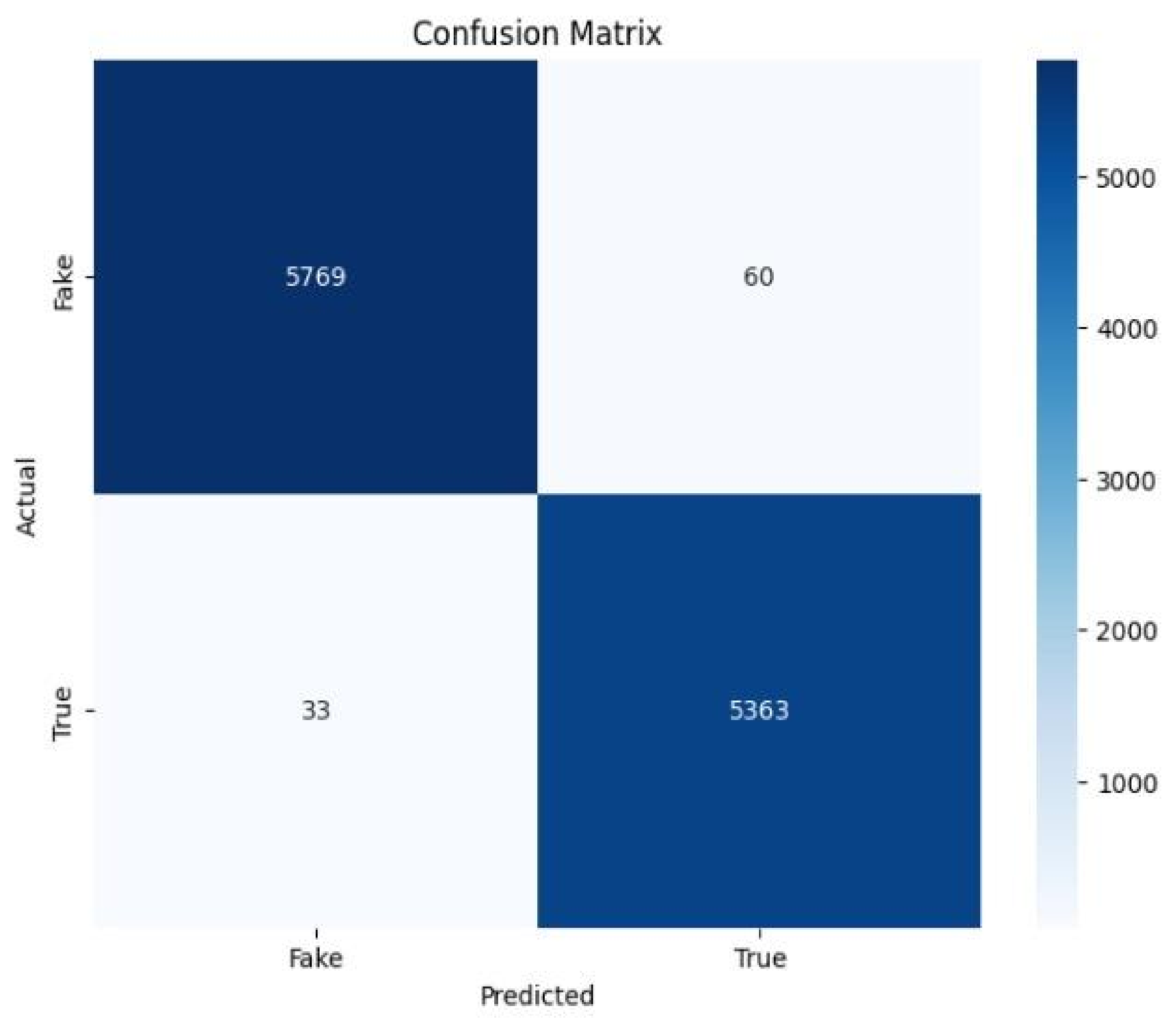


Figure: Confusion Matrix of Logistic Regression

Confusion Matrix(Contd.)

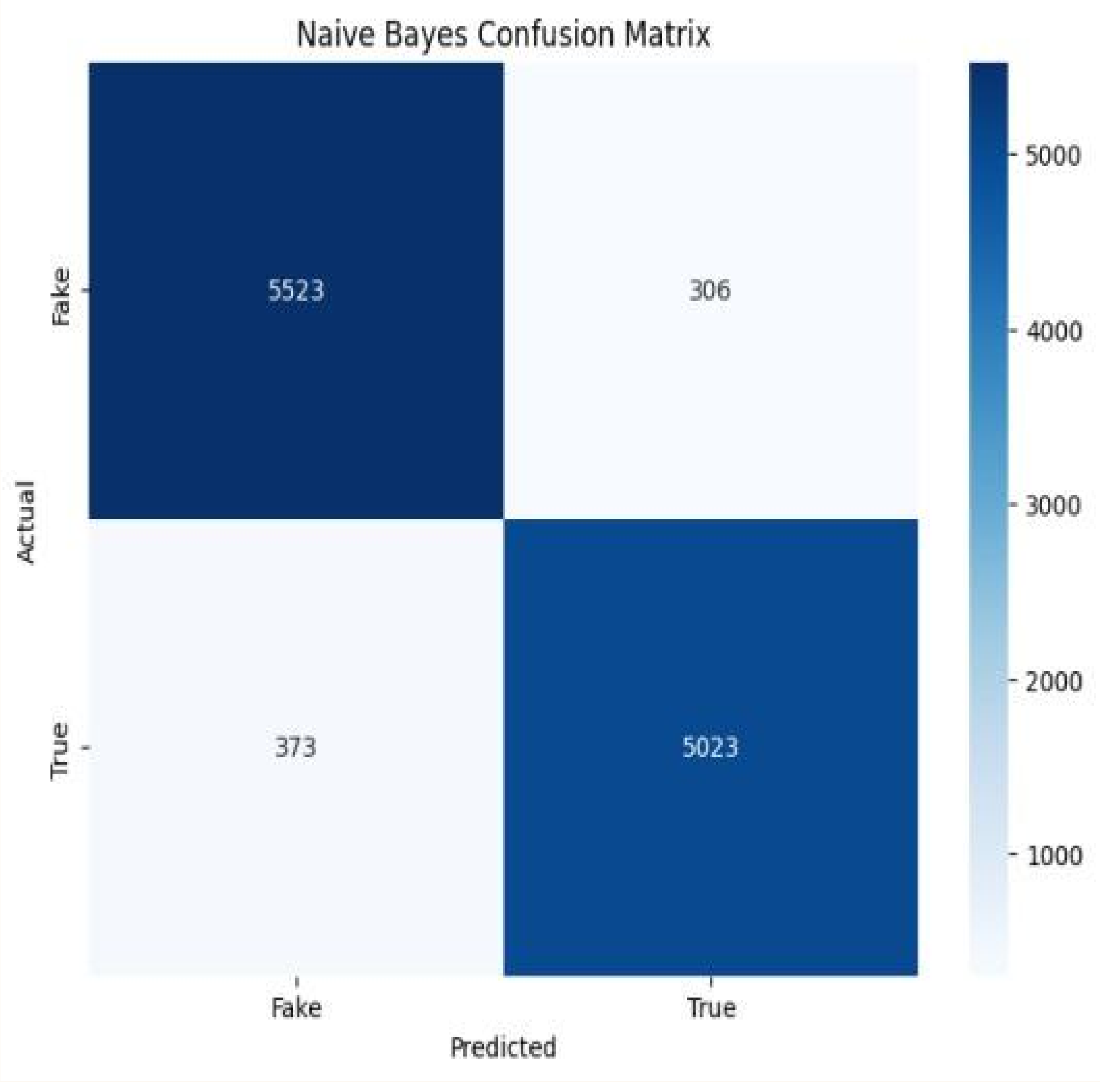


Figure: Confusion Matrix of Naive Bayes

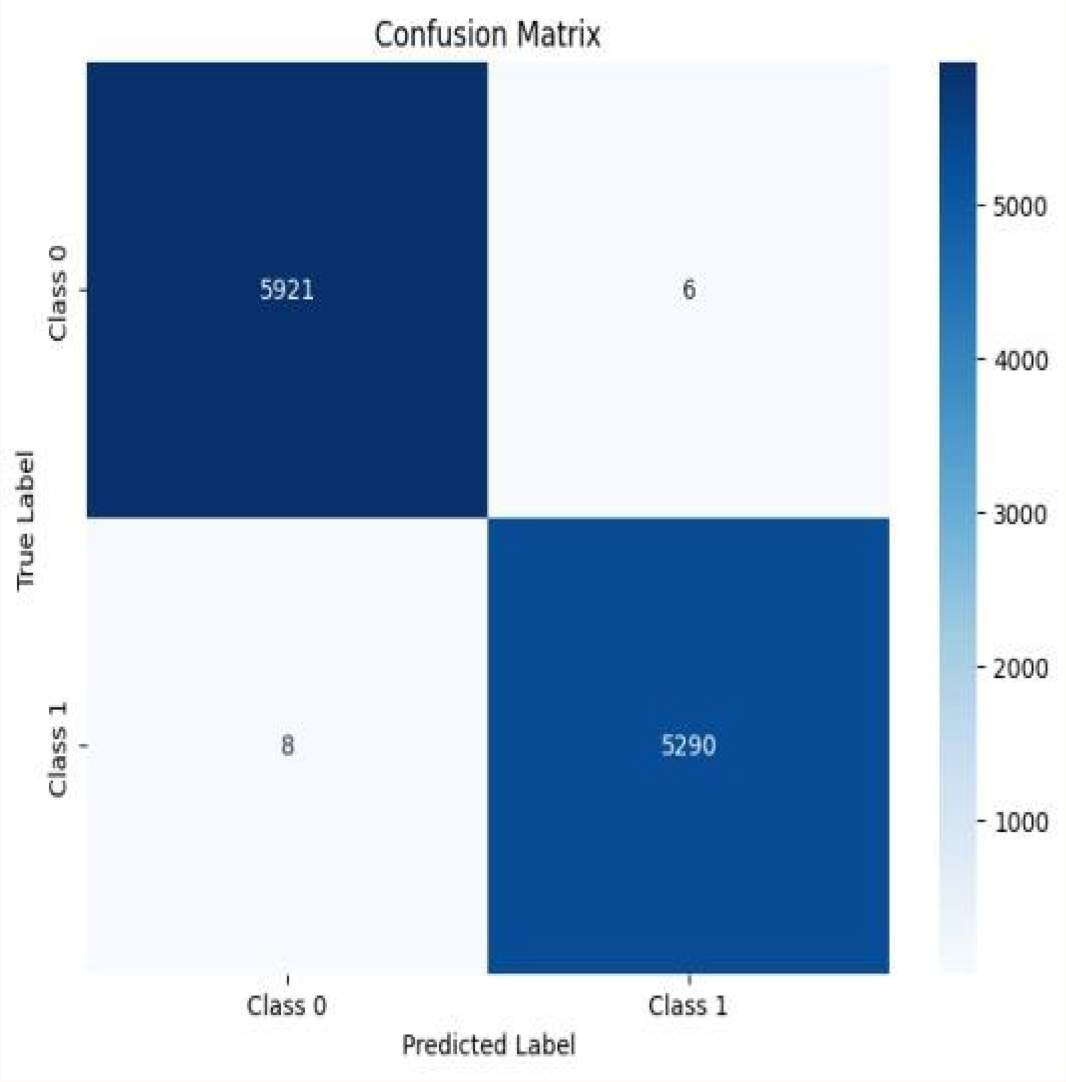


Figure: Confusion Matrix of LSTM

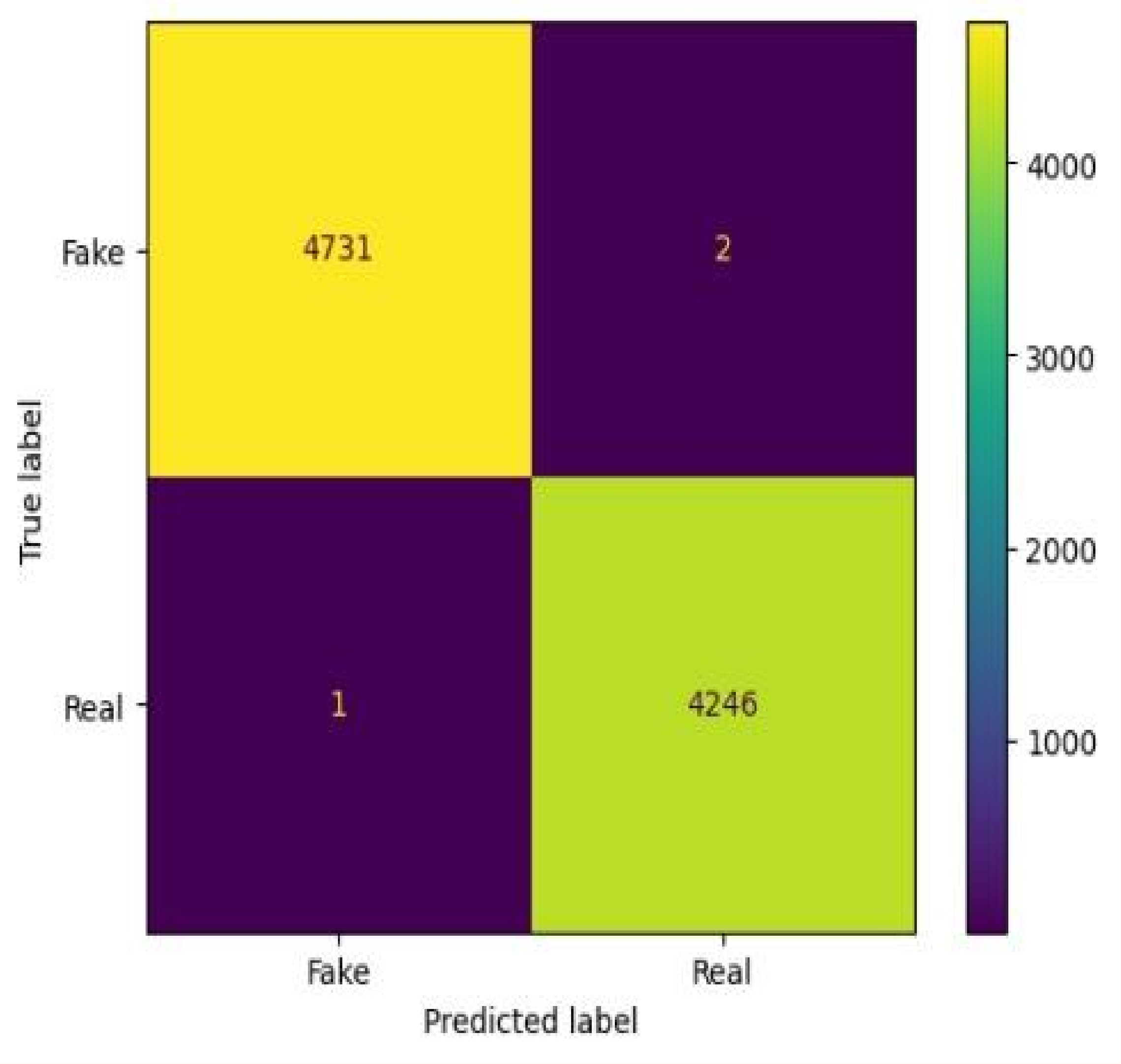


Figure: Confusion Matrix of BERT

ROC Curve

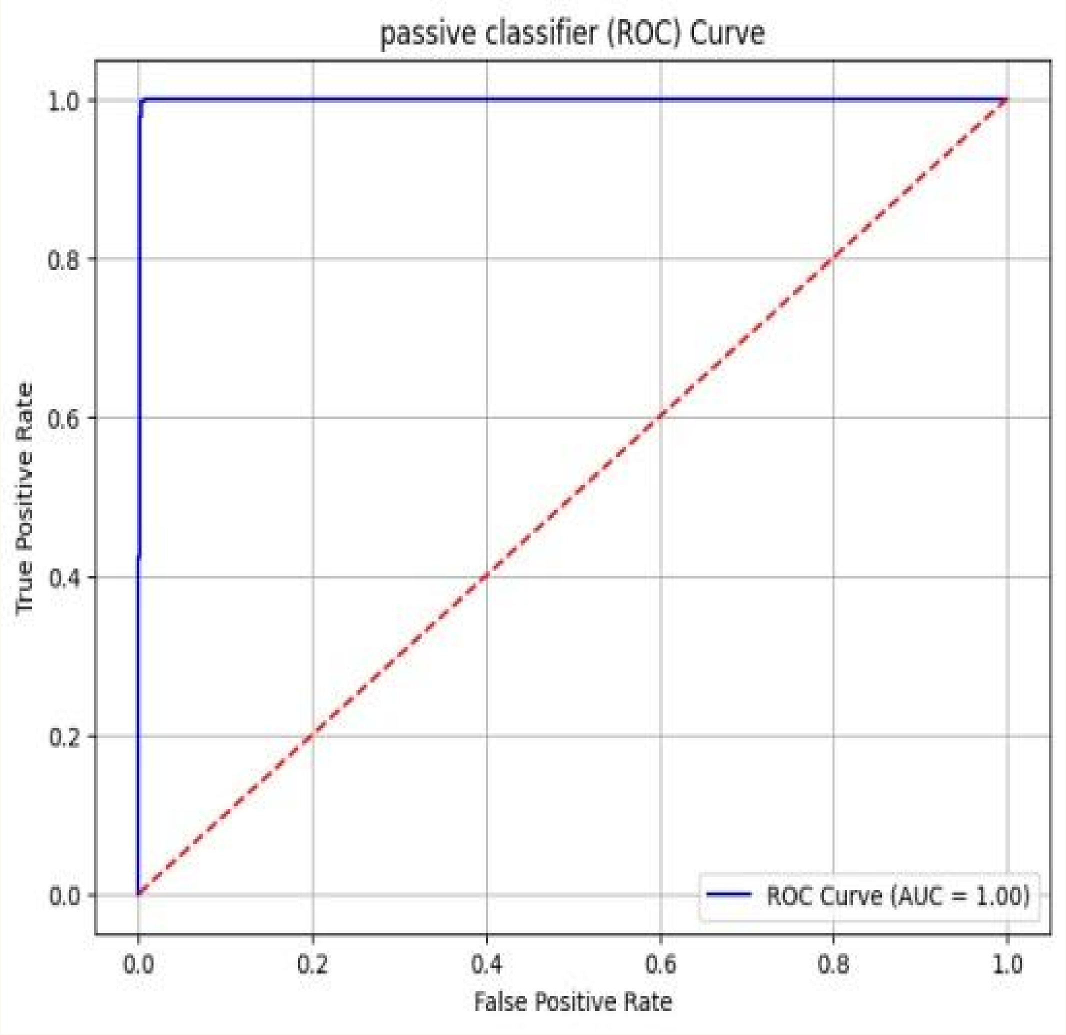


Figure : ROC Curve for PAC

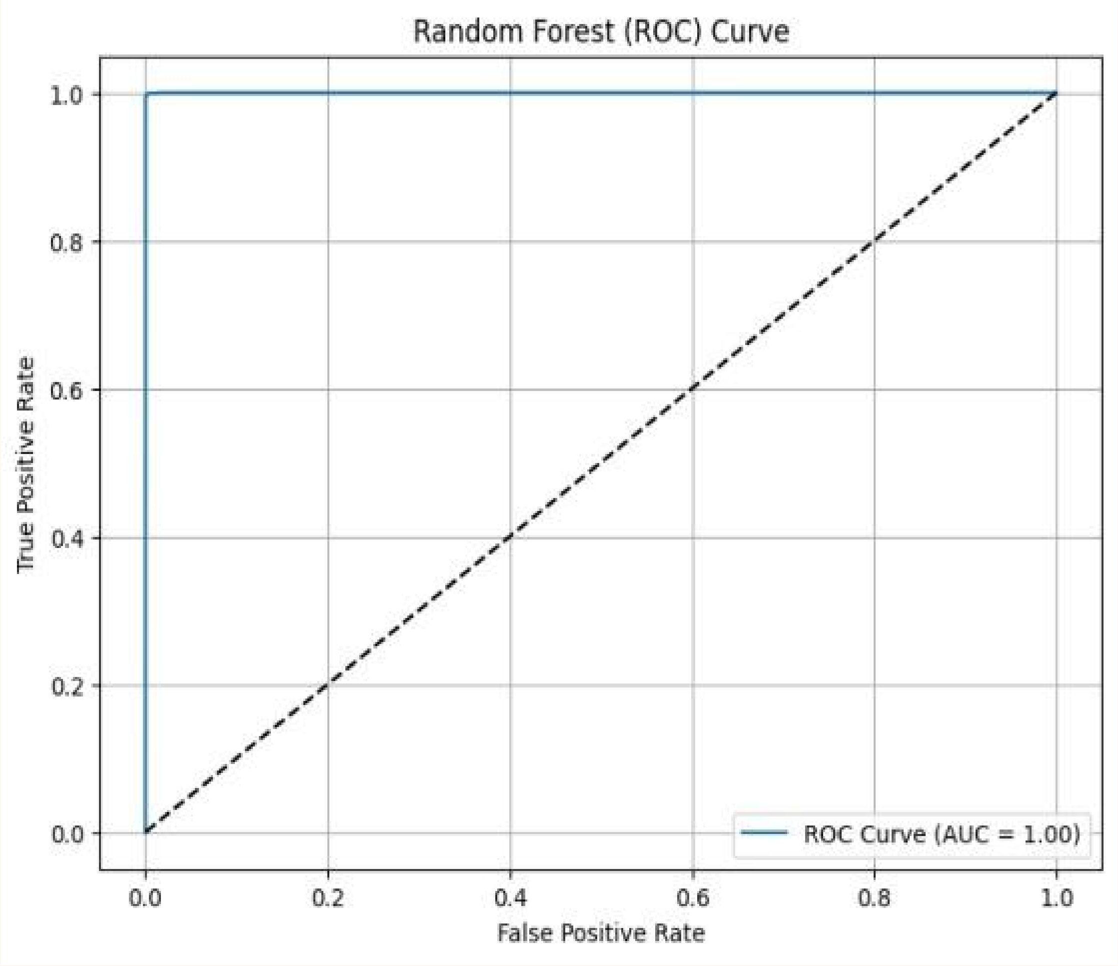


Figure : ROC Curve for RF

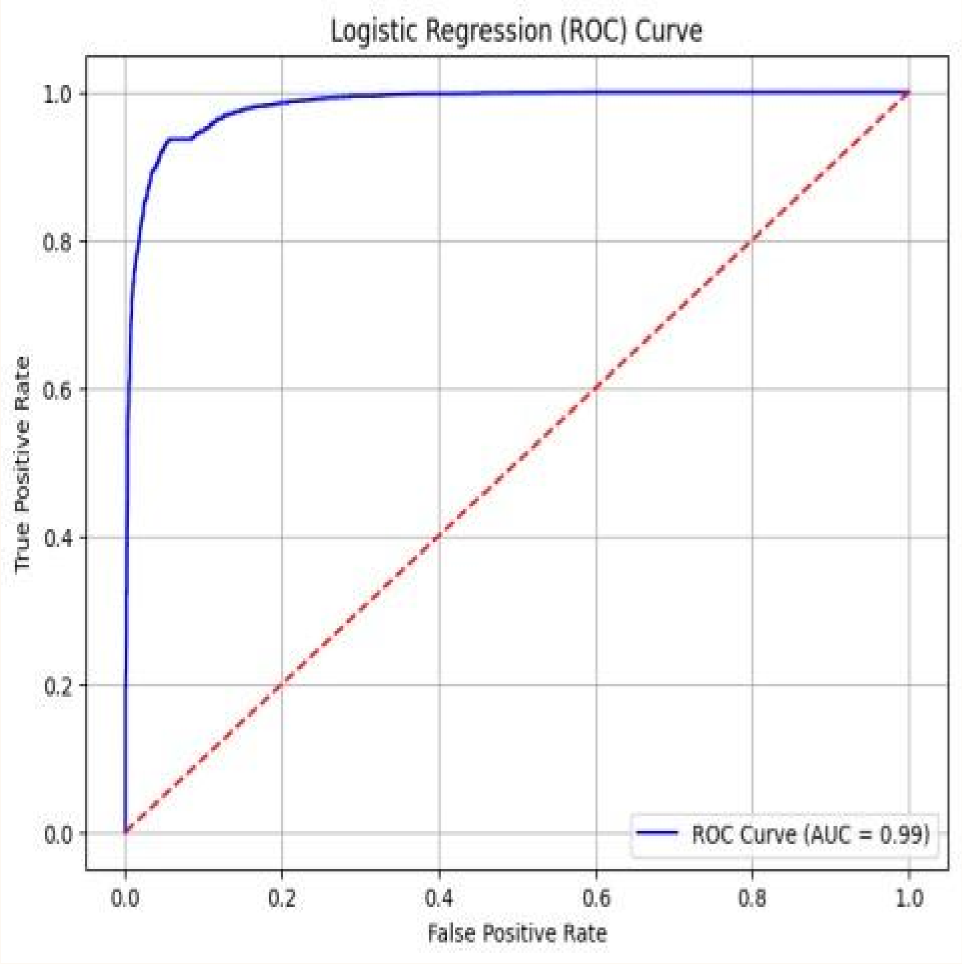


Figure: ROC Curve for LR

ROC Curve(Contd.)

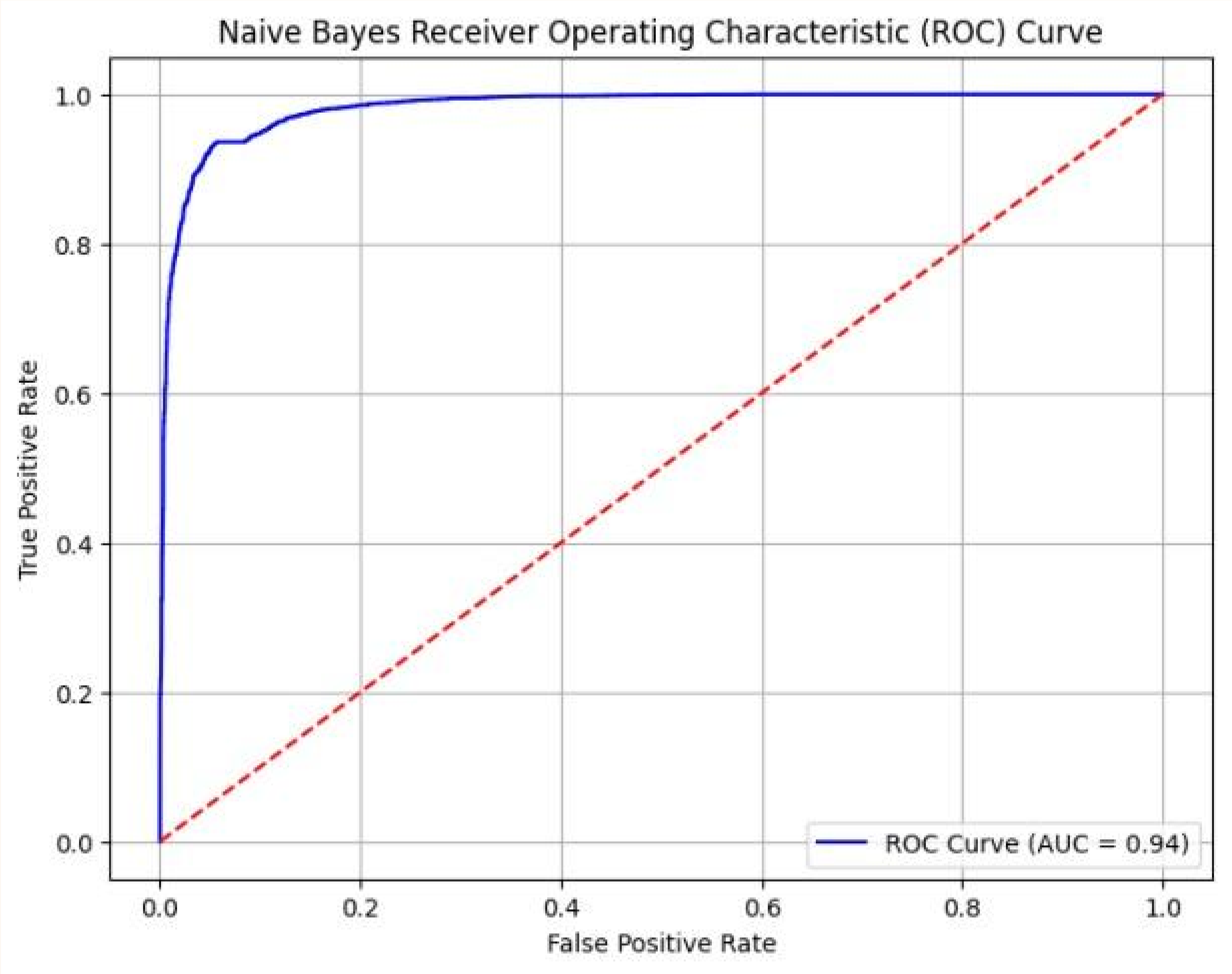


Figure : ROC Curve for NB

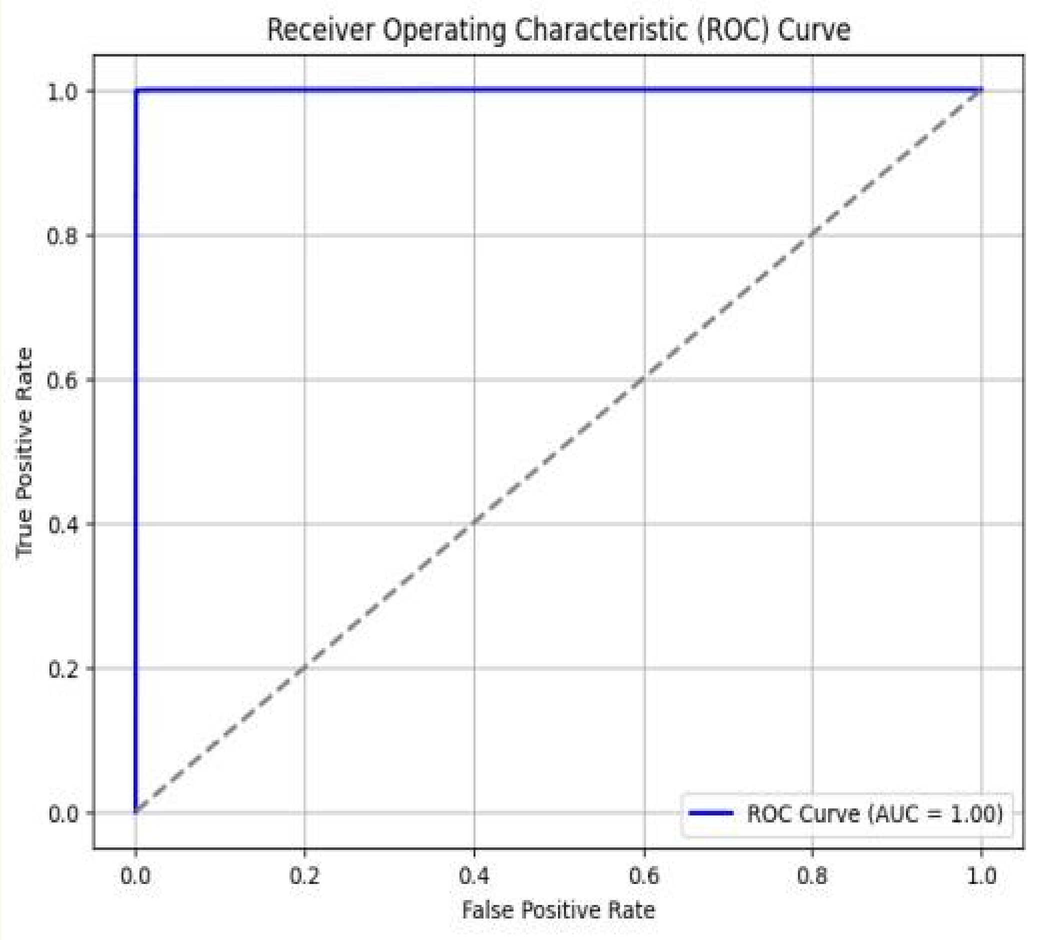


Figure : ROC Curve for LSTM

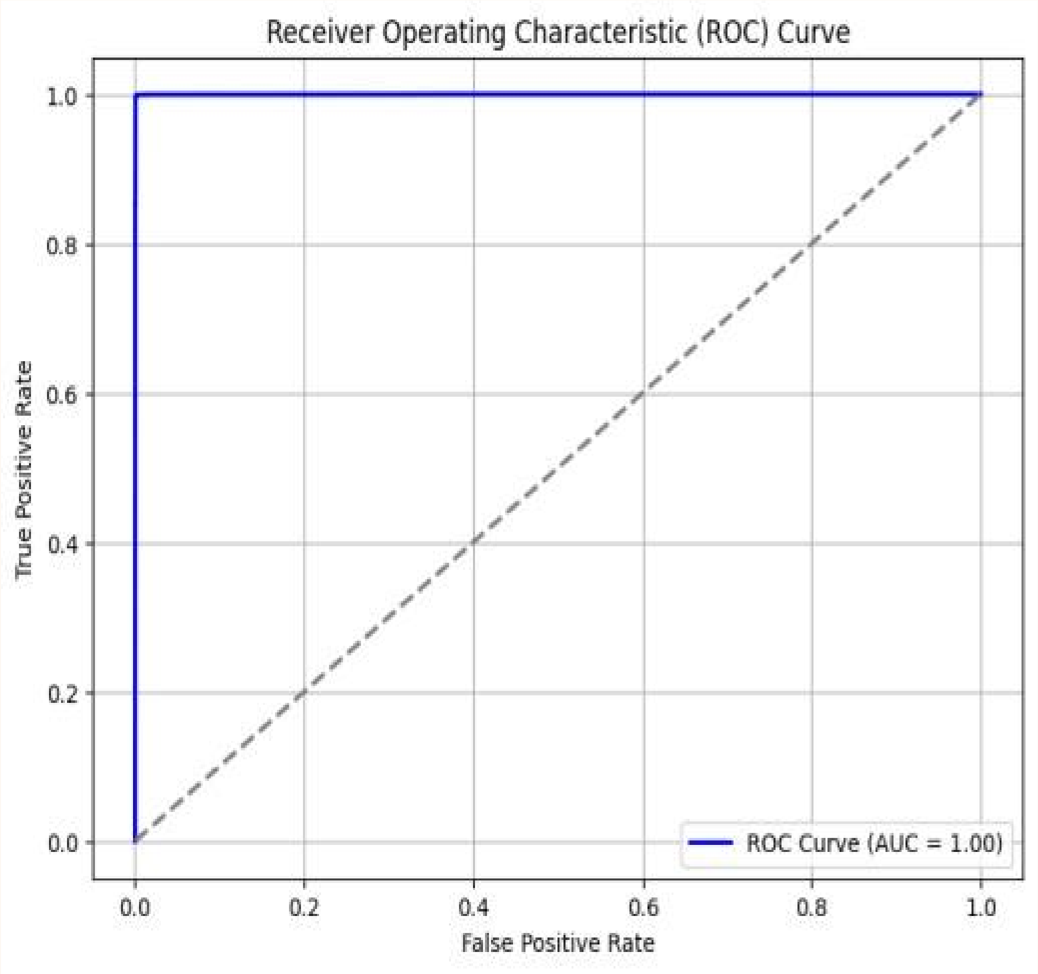


Figure: ROC Curve for BERT

RESULT

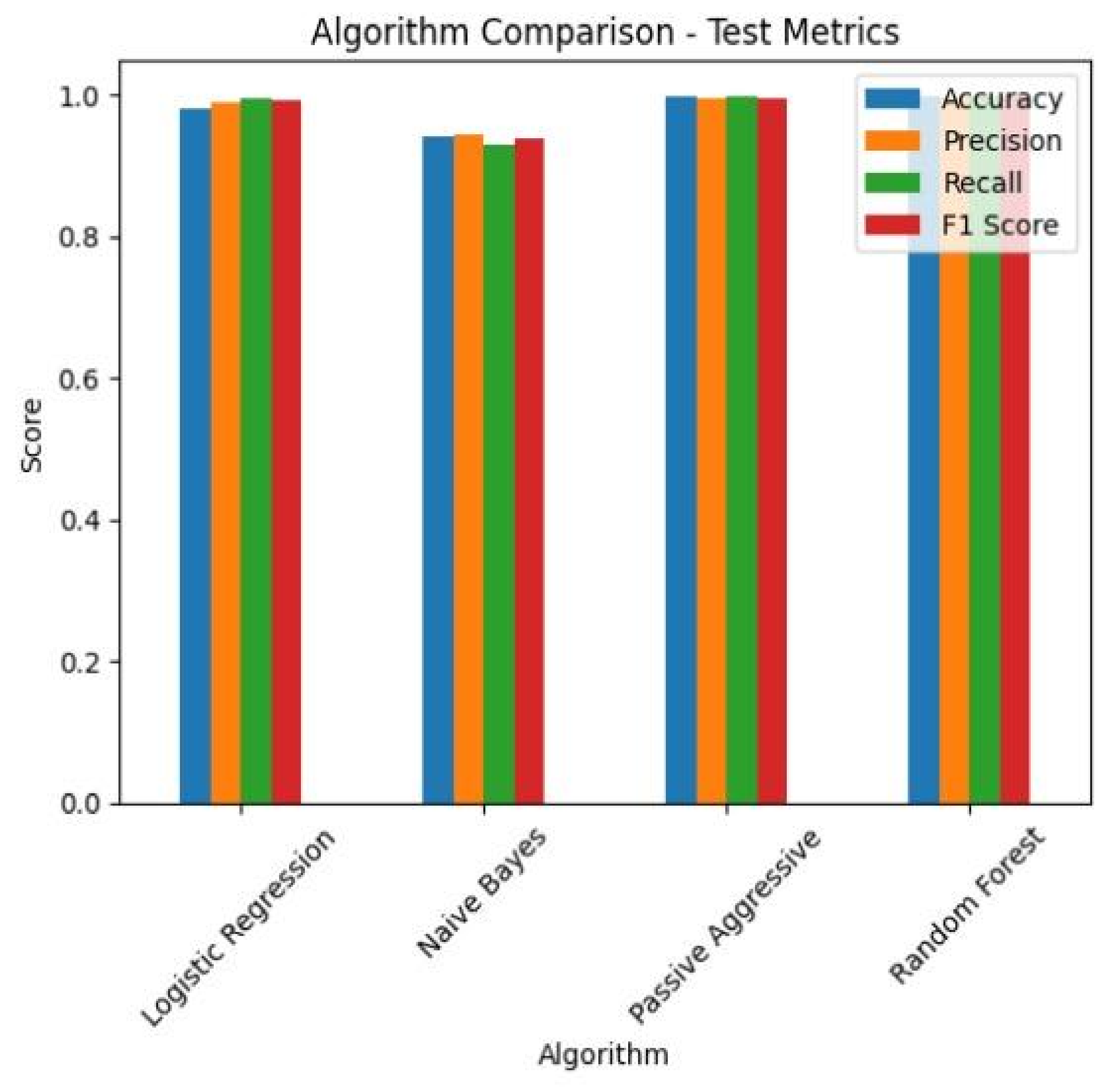


Figure: Overall Comparison of Four ML Models Evaluation Metrics

Model Name	Accuracy	Precision	Recall	F1 Score
PassiveAggressive Classifier	100%	100%	100%	100%
Random Forest	100%	100%	100%	100%
Logistic Regression	99%	99%	99%	99%
Naïve Bayes	94%	94%	95%	94%
LSTM	100%	100%	100%	100%
BERT	100%	100%	100%	100%

Table: Comparative Analysis of ML & DL Models

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 700, 100)	10,660,000
lstm (LSTM)	(None, 128)	117,248
dense (Dense)	(None, 1)	129

```
Total params: 11,012,133 (42.01 MB)
Trainable params: 117,377 (458.50 KB)
Non-trainable params: 10,660,000 (40.66 MB)
Optimizer params: 234,756 (917.02 KB)
```

Figure : Model Summary of LSTM

RESULT(LIME)

Explainable AI (XAI) enhances transparency and trust by making machine learning model decisions understandable to human. In fake news detection, LIME explains why a model labels news as fake or real by highlighting key features or words, ensuring transparency and trust.

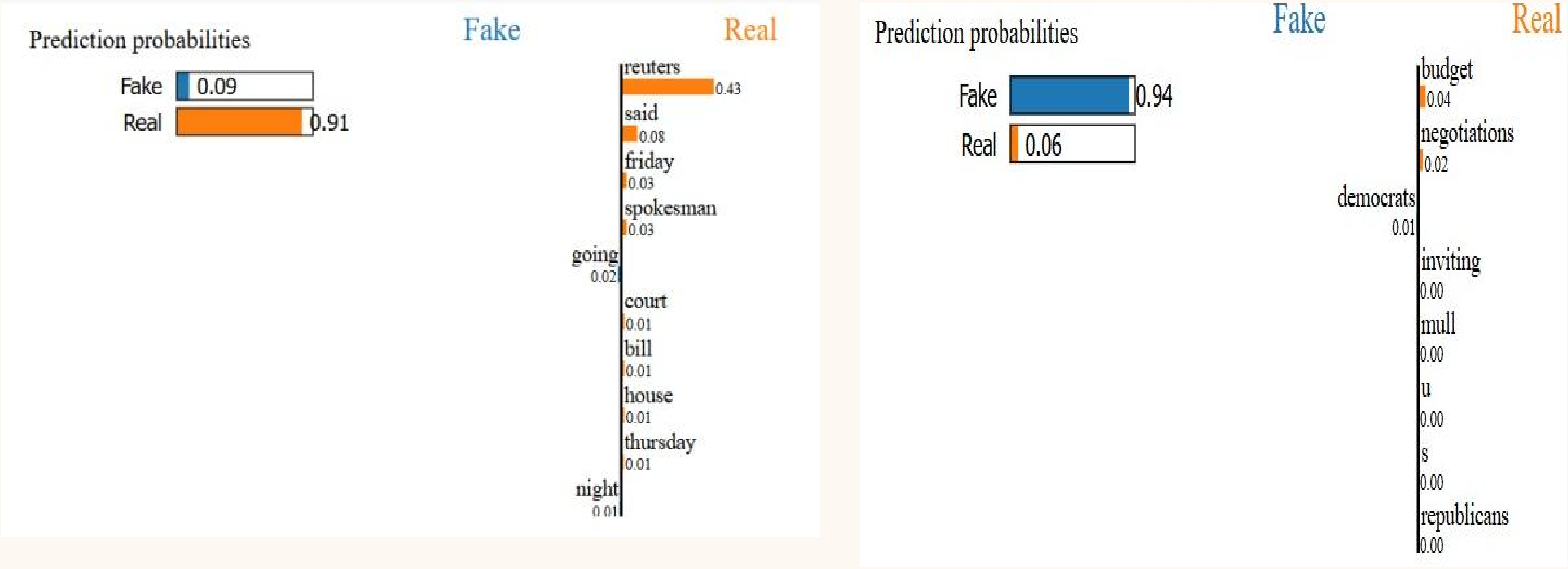


Figure: : LIME explanations for prediction probabilities for both classes(Real & Fake)

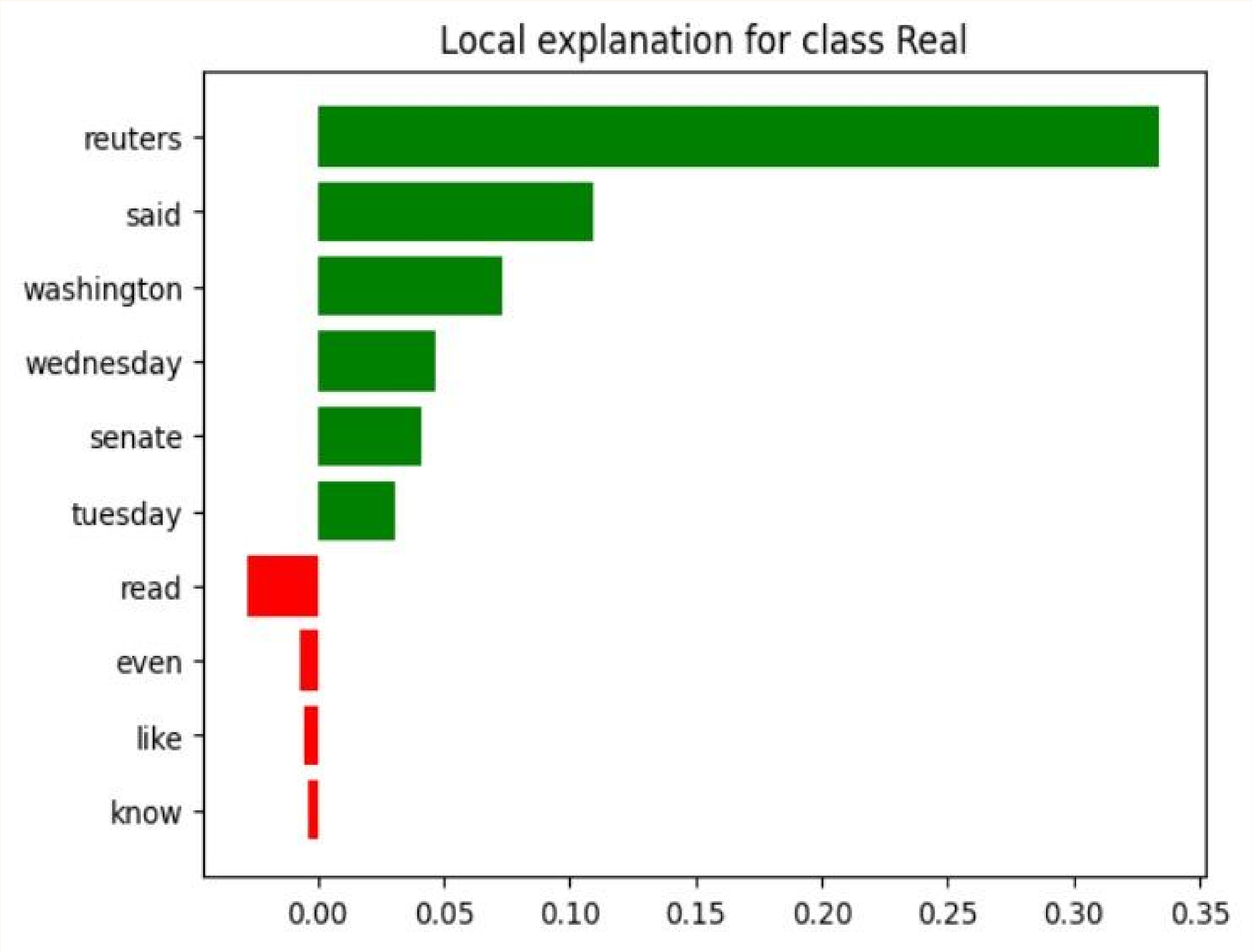
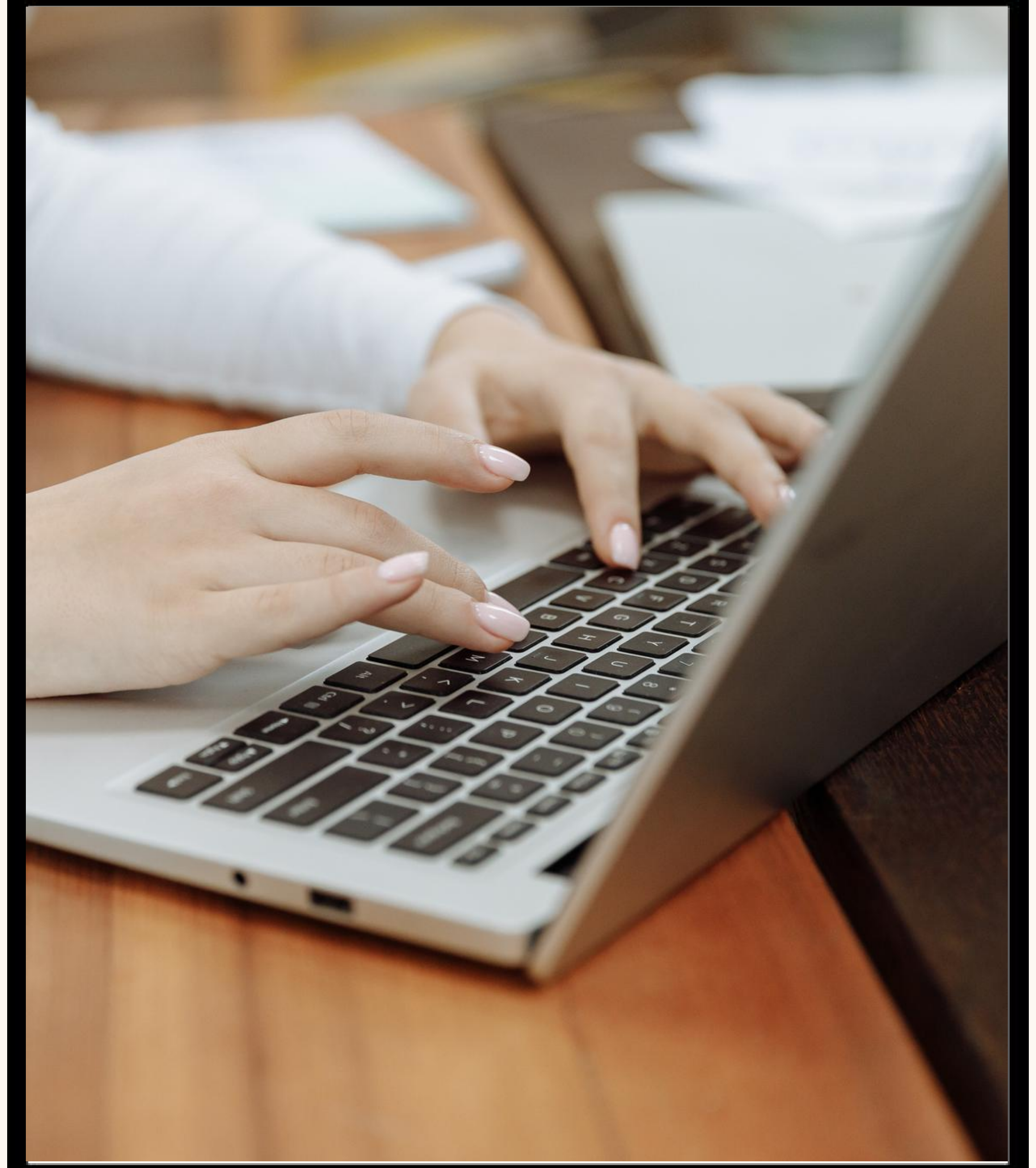


Figure: Top Influential Words for Classifying News as Real Using LIME Explanation

CONCLUSION

Our research successfully demonstrates the detection of fake news using ML, DL, and XAI techniques, achieving an impressive 100% accuracy. Models such as Random Forest, Passive Aggressive Classifier, LSTM, and BERT delivered outstanding performance in classification tasks. The incorporation of XAI methods like LIME ensured transparency, interpretability, and trust in the model's decisions

Future Work



- ❑Exploration of **Multimodal Detection** Approaches.
- ❑Development of **Cross-Lingual** and Cross-Cultural Detection.
- ❑Advancements in **Real-Time** Detection.
- ❑Integration of Fake News Detection with **Social Media** Platforms.
- ❑Utilization of **User Behavior Analysis** for Fake News Detection.

References

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- Kumar, K. J., Shreya, K., Divakarla, L. P., Nair, P. C., & Sampath, N. (2024, June). Interpretable AI Insights in Fake News Detection: A Comparative Analysis of CNN and LSTM. In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.
- N. Tabassoum and M. A. Akber, "Interpretability of machine learning algorithms fornews category classification using xai," in 2024 6th International Conference on Electrica lEngineering and Information & Communication Technology (ICEEICT). IEEE, 2024,pp. 770–775.

THANK YOU SO MUCH!