Fake Covid NEWS

DETECTION

GROUP 2

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RESEARCH BACKGROUND

Social media's fast-paced, bite-sized news fosters emotional engagement but discourages critical thinking, making users more susceptible to fake news.

PROBLEM STATEMENT

- Fake news increasingly mimics credible sources, making detection harder and requiring better verification methods.

- Fake COVID-19 news spreads misinformation, causing public confusion and distrust in health authorities.

- Social media accelerates fake news, emphasizing the need for strong detection systems to ensure accuracy.

OBJECTIVE

- Evaluate the effectiveness of different algorithms in detecting sophisticated fake news.
- Compare accuracy, efficiency, and robustness across various detection models.
- Identify the most suitable algorithm for reliable and scalable fake news detection.

LITERATURE REVIEW

Source	Year	Purpose	Methods	Findings	Meaning
Natali Ruchansky, Sungyong Seo, Yan Liu; CSI: A Hybrid Deep Model for Fake News Detection	2017	Propose a hybrid model detecting fake news combining of text content, user response, and user behavior	Use deep learning with three components of capture, score, and integrate	CSI model improves fake news detection using multiple data sources	Using text, user response, and behavior data greatly enhances compared to text only
Akshay Jain & Amey Kasbe; Fake News Detection	2018	To develop a fake news detection model using machine learning	Naïve Bayes Classifier, Web Scraping, Bag-of-Words, N-grams	Achieved 0.931 AUC score with n-grams full-text classification performed better than titles	Full-text analysis is more reliable than headlines. N-grams improve performance.
Sherry Girgis, Eslam Amer, Mahmoud Gadallah; Deep Learning Algorithms for Detecting Fake News in Online Text	2018	To analyze the effectiveness of different deep learning models (RNNs, LSTMs, GRUs, CNNs) for deception detection.	Use of 12.8K LIAR datasets, data preparation techniques, and evaluation of models with accuracy and F-score metrics.	Type(Acc, F-Score) • RNN (85%, 0.82) • LSTM (88%, 0.85) • GRU (87%, 0.84) • CNN (83%, 0.80)	Since LSTM and GRU outperform RNN and CNN in deception detection, it makes sequence based model better as the other two use spatial feature exration

LITERATURE REVIEW

Source	Year	Purpose	Methods	Findings	Meaning
Haumahu et al. (IOP Conf. Ser.: Mater. Sci. Eng., 1098) Using Extreme Gradient Boosting (XGBoost)	2021	Classify Indonesian news as real or fake using XGBoost.	Analyzed 500 news articles with TF-IDF and XGBoost.	Achieved 89% accuracy, outperforming Naive Bayes and KNN.	Confirms XGBoost's effectiveness in identifying Indonesian fake news.
Nistor & Zadobrischi (Sustainability, 14, 10466) The Influence of Fake News on Social Media...	2022	Analyze fake news impact on social media during COVID-19 and propose detection solutions.	Used machine learning, NLP, and CNN to detect fake news on Facebook.	Improved accuracy over conventional methods, highlighting AI's role in combating misinformation.	Shows how fake news spreads and presents AI-driven detection, stressing digital literacy.
Essa et al. (Complex & Intelligent Systems, 1098) Hybrid BERT and LightGBM models...	2023	Develop an efficient fake news detection system.	Combined BERT and LightGBM, tested on three datasets against traditional models.	Outperformed Naive Bayes, SVM, and LSTM, improving accuracy and efficiency.	Transformer models like BERT with LightGBM enhance fake news detection, offering a strong solution.

DATASET AND PREPROCESSING

Overview: This dataset contains 8000 news data with features of title, tweet, and label.

Data Splitting: 60% Training data, 20% Validation Data, and 20% Testing data

	id	tweet	label
0	1	The CDC currently reports 99031 deaths. In gen...	real
1	2	States reported 1121 deaths a small rise from ...	real
2	3	Politically Correct Woman (Almost) Uses Pandem...	fake
3	4	#IndiaFightsCorona: We have 1524 #COVID testin...	real
4	5	Populous states can generate large case counts...	real

DATA PREPROCESSING

- Removing special characters
- Convert to lowercase
- Check for missing values
- Remove extra whitespaces and line break from text
- Normalizing multiple punctuation into single punctuation

PREDICTION MODEL

- **Tokenization Methods Used:**
  - **BERT** for Context-aware tokenization using deep learning
  - **TF-IDF** for Traditional frequency-based tokenization

- **CLASSIFICATION ALGORITHM USE:**
  - **Naïve Bayes Classifier for** Probabilistic model for text classification
  - **Gradient Boosting (XGBoost)** for Powerful ensemble learning technique

HYPERPARAMETER TUNING

- **Tool Used: GridSearchCV**
- **Model Tuned: XGBoost Classifier**
- **Key Hyperparameters Optimized:**

  - **N_estimators** for Number boosting rounds
  - **Max_depth** for Maximum dept of trees
  - **Learning_rate** for Step size shrinkage to prevent overfitting
  - **Subsample** for Fraction of samples used per boosting round
  - **Colsample_bytree** for Fraction of features used per tree

Hyperparameter tuning for Naïve Bayes Classifier includes:

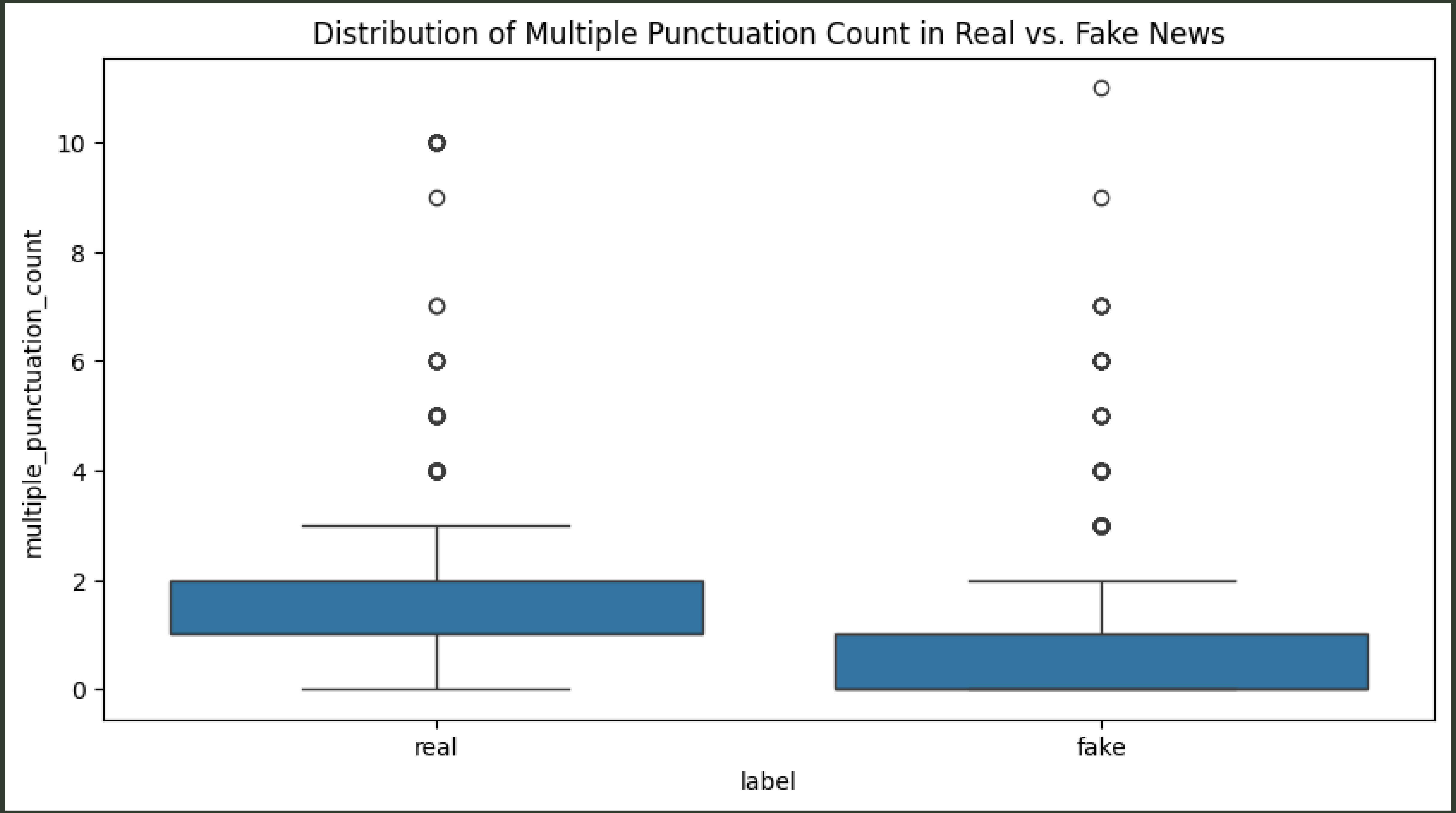
- **Alpha: is a parameter for controlling the level of smoothness of applied to probabilities. Adding alpha ensures word that does not appear get a small amount of non-zero probability**

EVALUATION METRICS

For assessing the performance of each model, the evaluation metric we are going to be used for each model is:

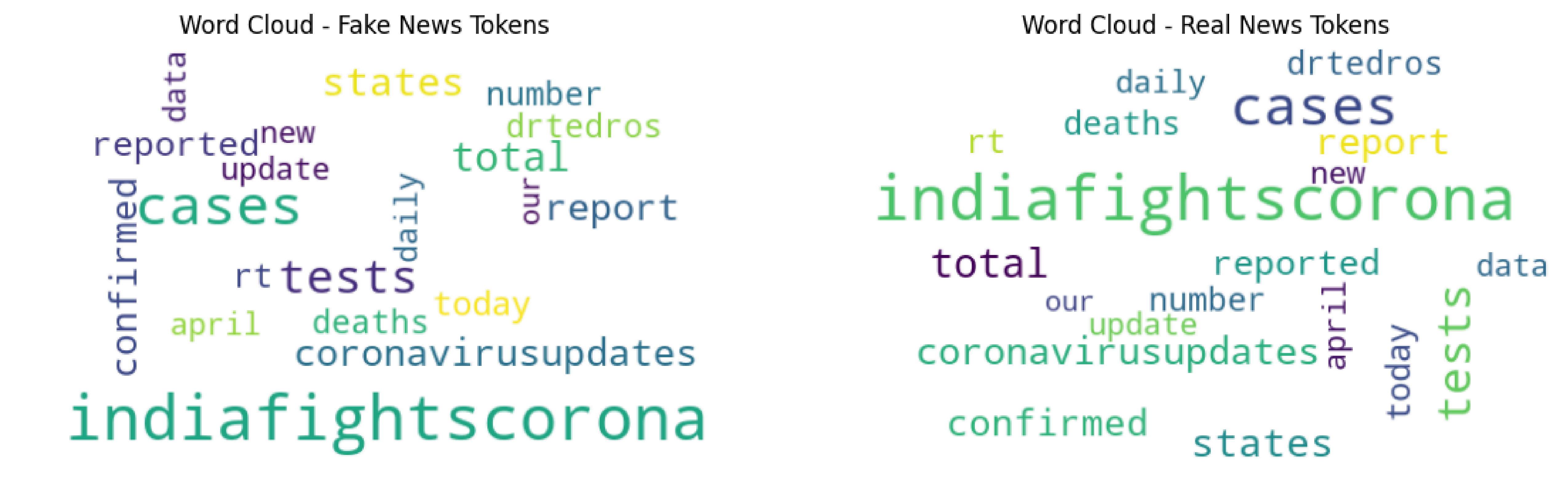
- Accuracy: Measures overall correctness of the model's predictions.
- Precision: Assesses the quality of positive predictions.
- Recall: Evaluates the model's ability to detect all positive instances.
- F1-Score: Balances precision and recall for overall performance.
- Confusion Matrix: Breaks down correct and incorrect classifications.
- ROC-AUC Score: Measures how well the model distinguishes between positive and negative classes.

RESULTS

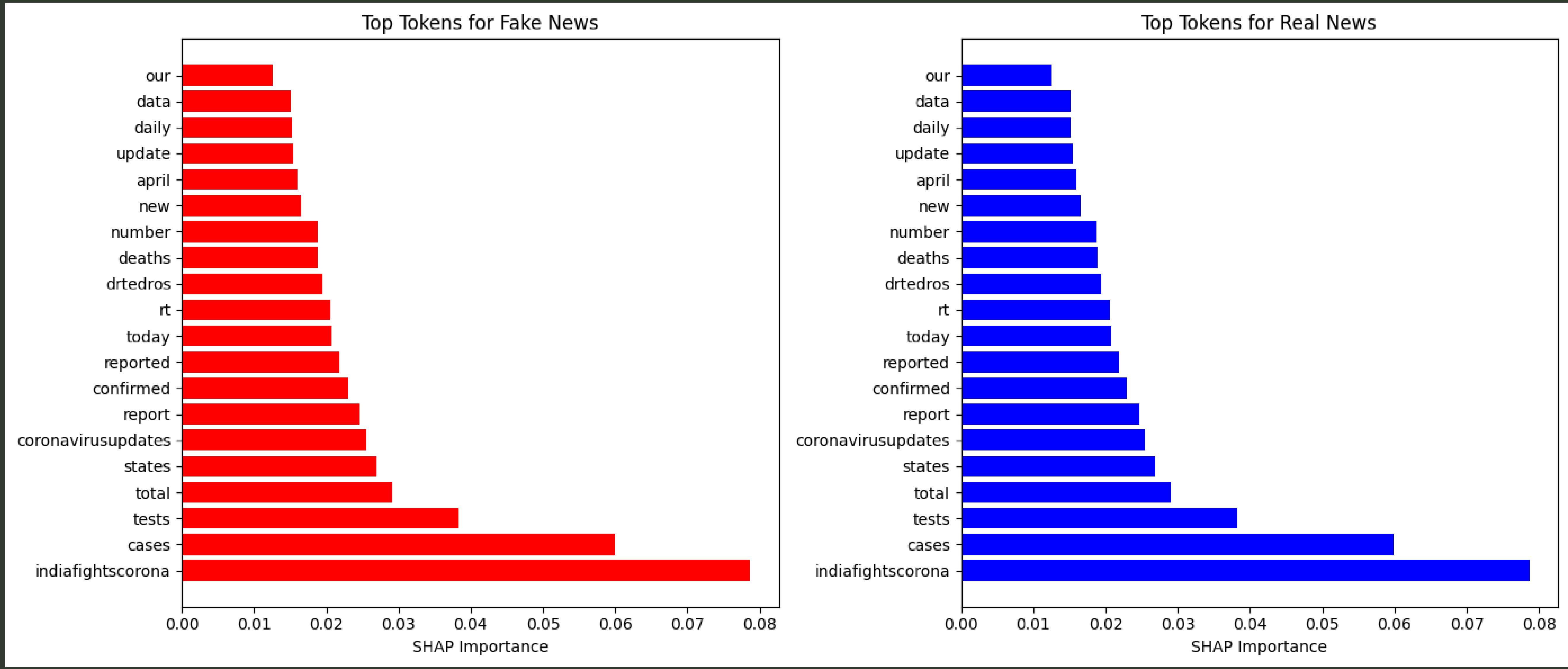


Distribution of Multiple Punctuation Count in Real vs. Fake News
multiple_punctuation_count
0
2
4
6
8
10
real
fake
label

RESULTS

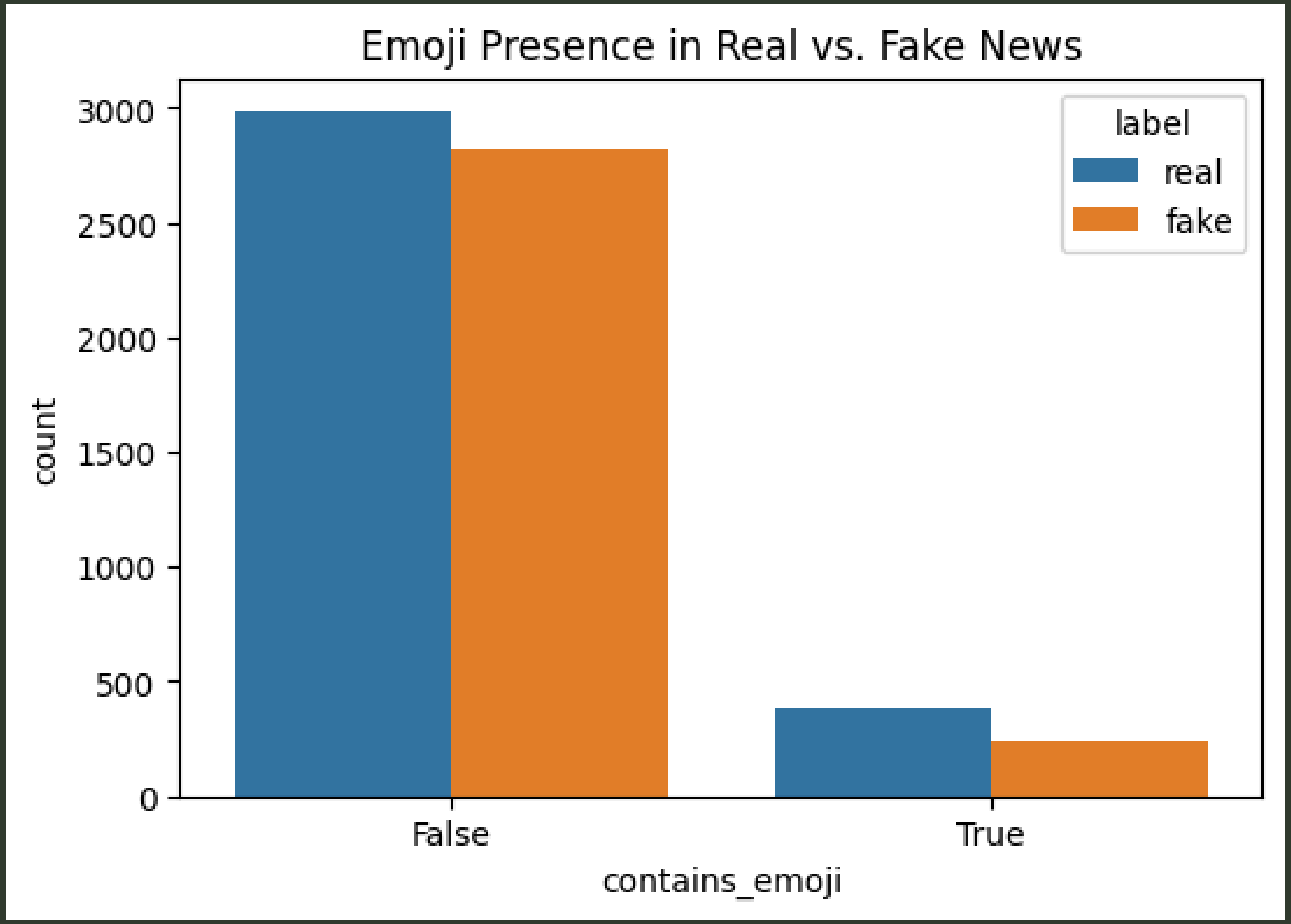

Word Cloud - Fake News Tokens
Word Cloud - Real News Tokens
indiafightscorona
cases
tests
total
states
number
drtedros
reported
new
update
report
our
daily
data
confirmed
rt
april
deaths
today
coronavirusupdates

RESULTS



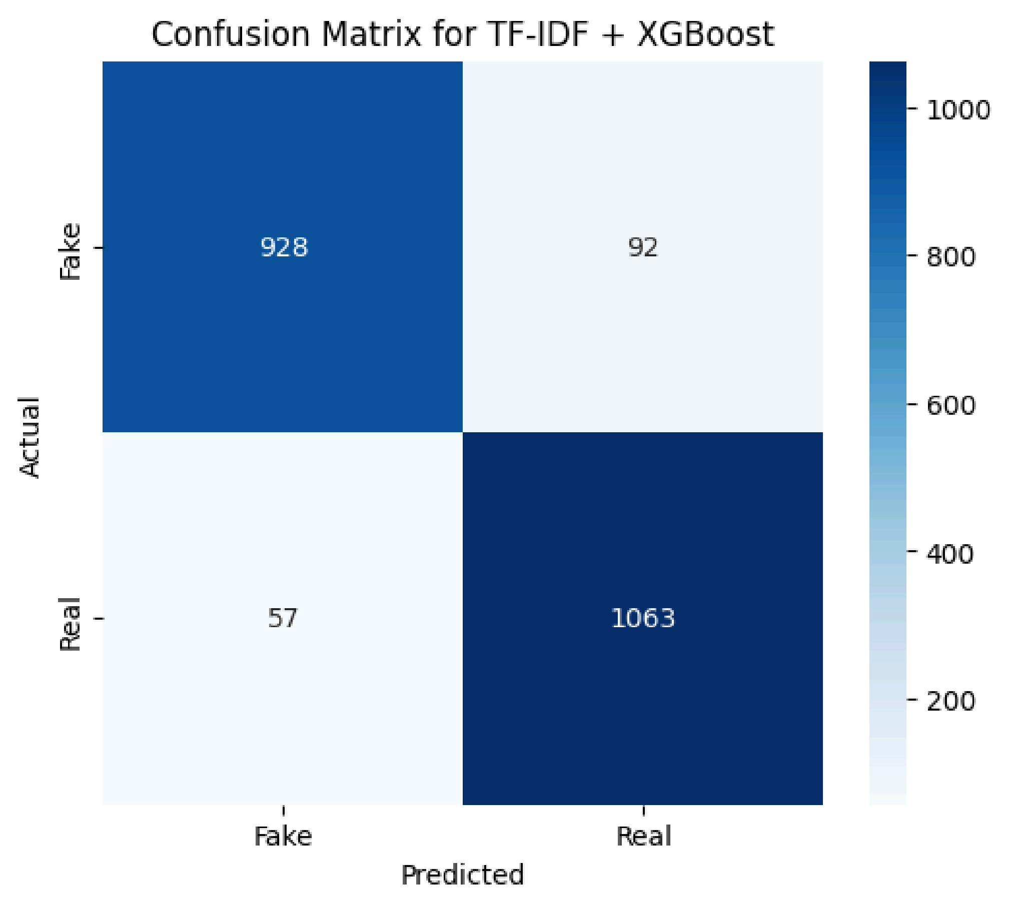
Top Tokens for Fake News
our
data
daily
update
april
new
number
deaths
drtedros
rt
today
reported
confirmed
report
coronavirusupdates
states
total
tests
cases
indiafightscorona
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08
SHAP Importance
Top Tokens for Real News
our
data
daily
update
april
new
number
deaths
drtedros
rt
today
reported
confirmed
report
coronavirusupdates
states
total
tests
cases
indiafightscorona
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08
SHAP Importance

RESULTS

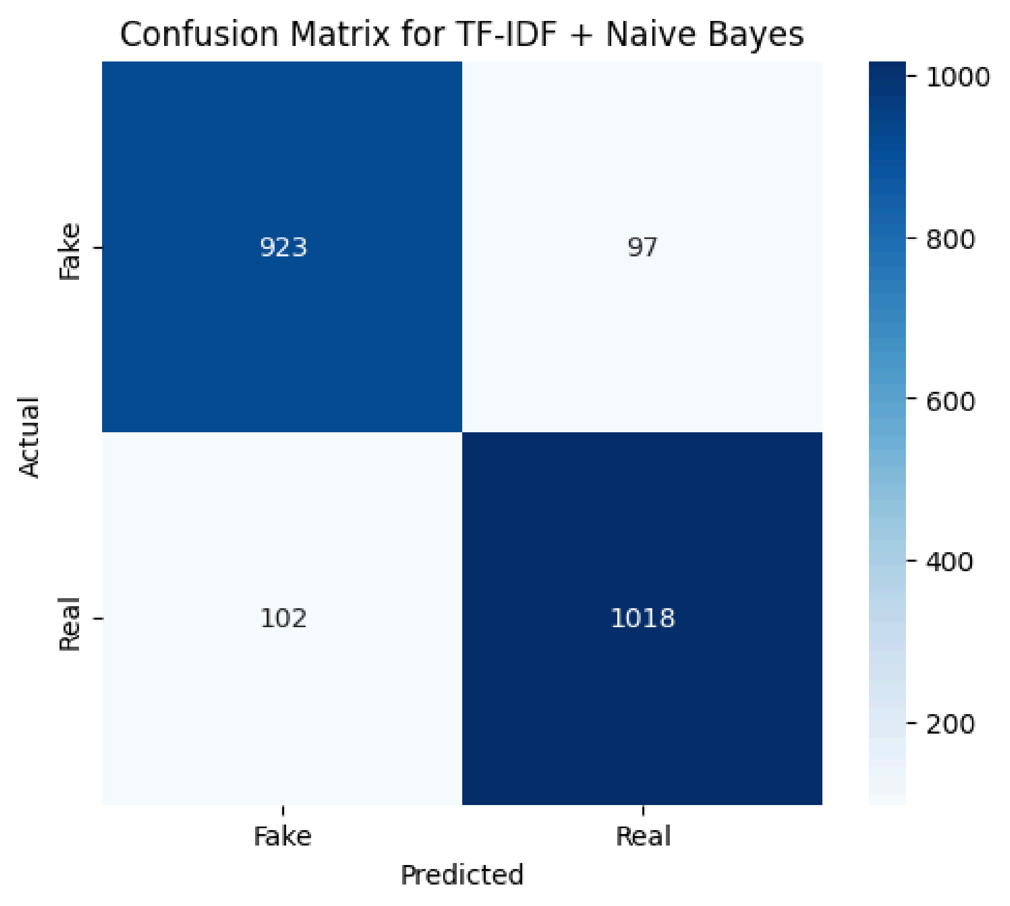


Emoji Presence in Real vs. Fake News
label
real
fake
3000
2500
2000
1500
1000
500
0
count
False
True
contains_emoji

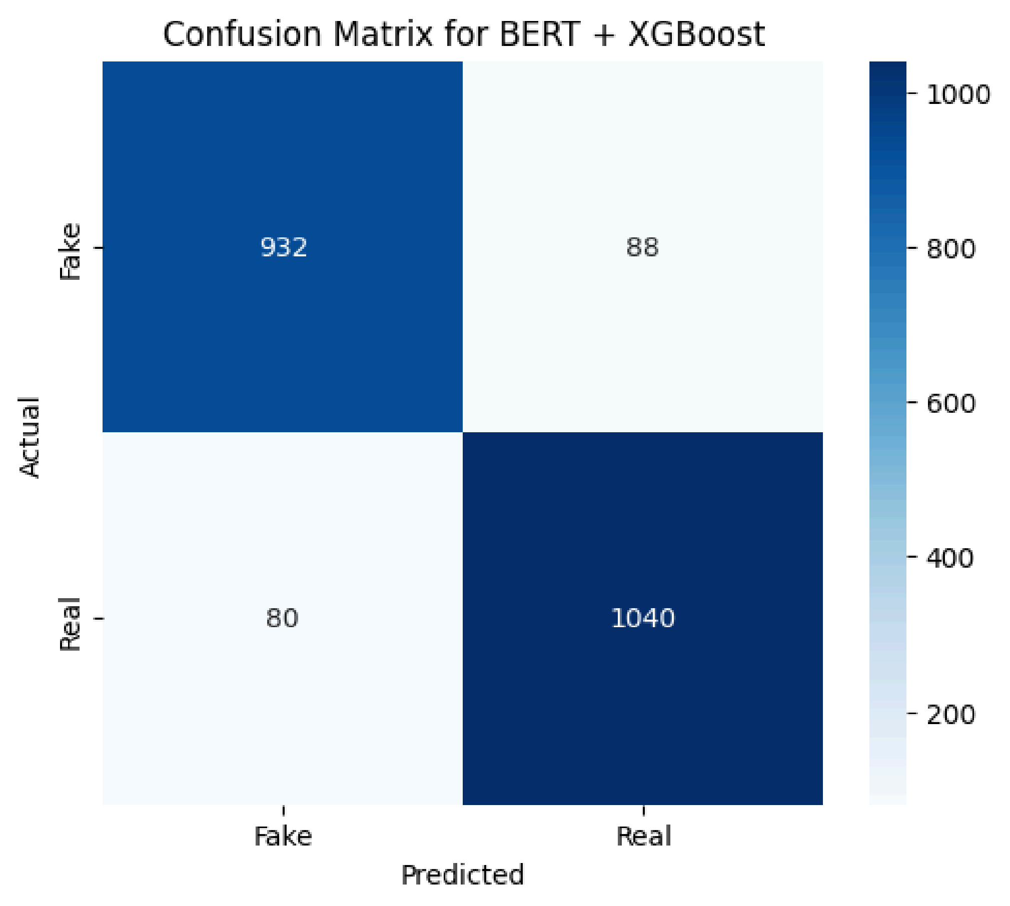
RESULTS



Confusion Matrix for TF-IDF + XGBoost
Actual
Predicted
Fake
Real
928
92
57
1063
1000
800
600
400
200



Confusion Matrix for TF-IDF + Naive Bayes
Actual
Predicted
Fake
Real
923
97
102
1018
1000
800
600
400
200

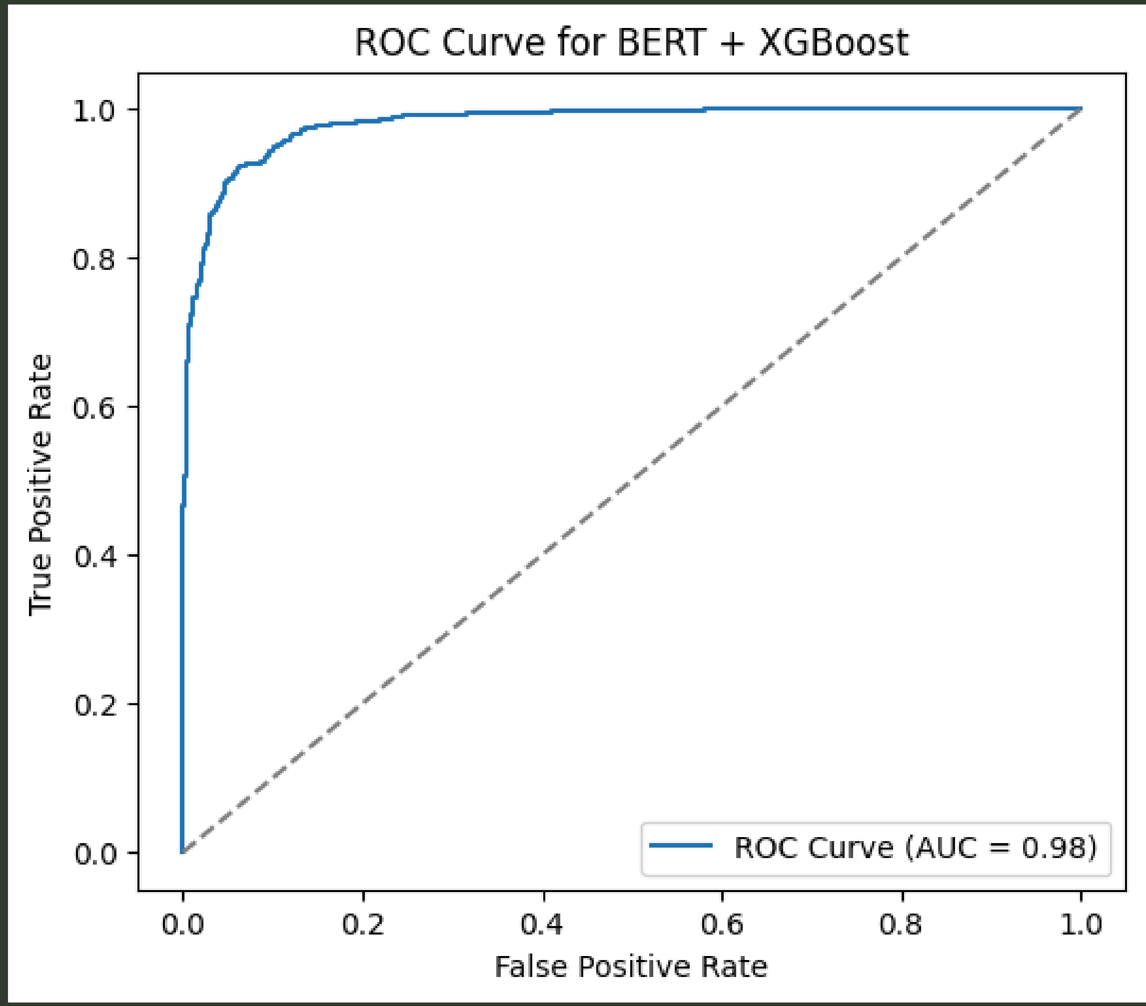


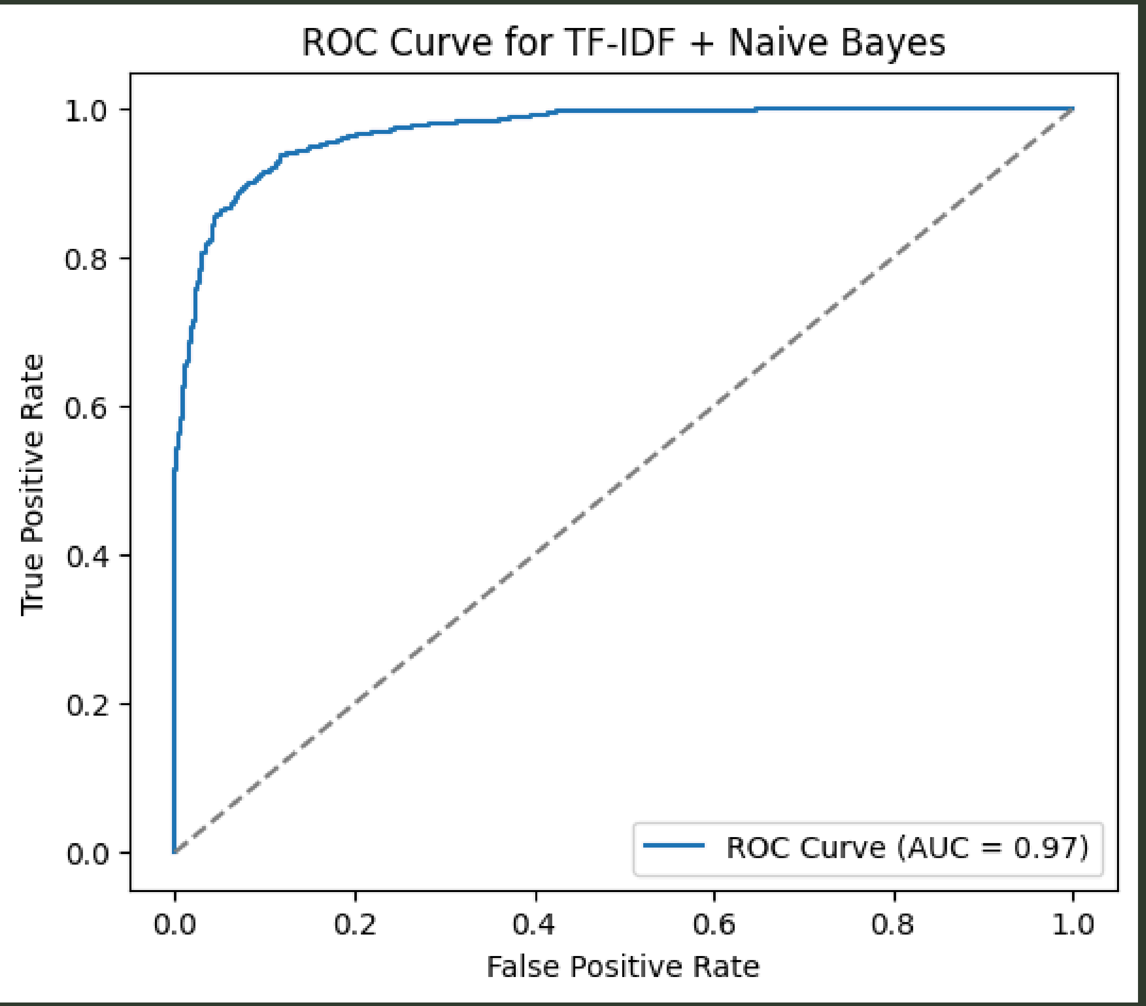
Confusion Matrix for BERT + XGBoost
Actual
Predicted
Fake
Real
932
88
80
1040
1000
800
600
400
200

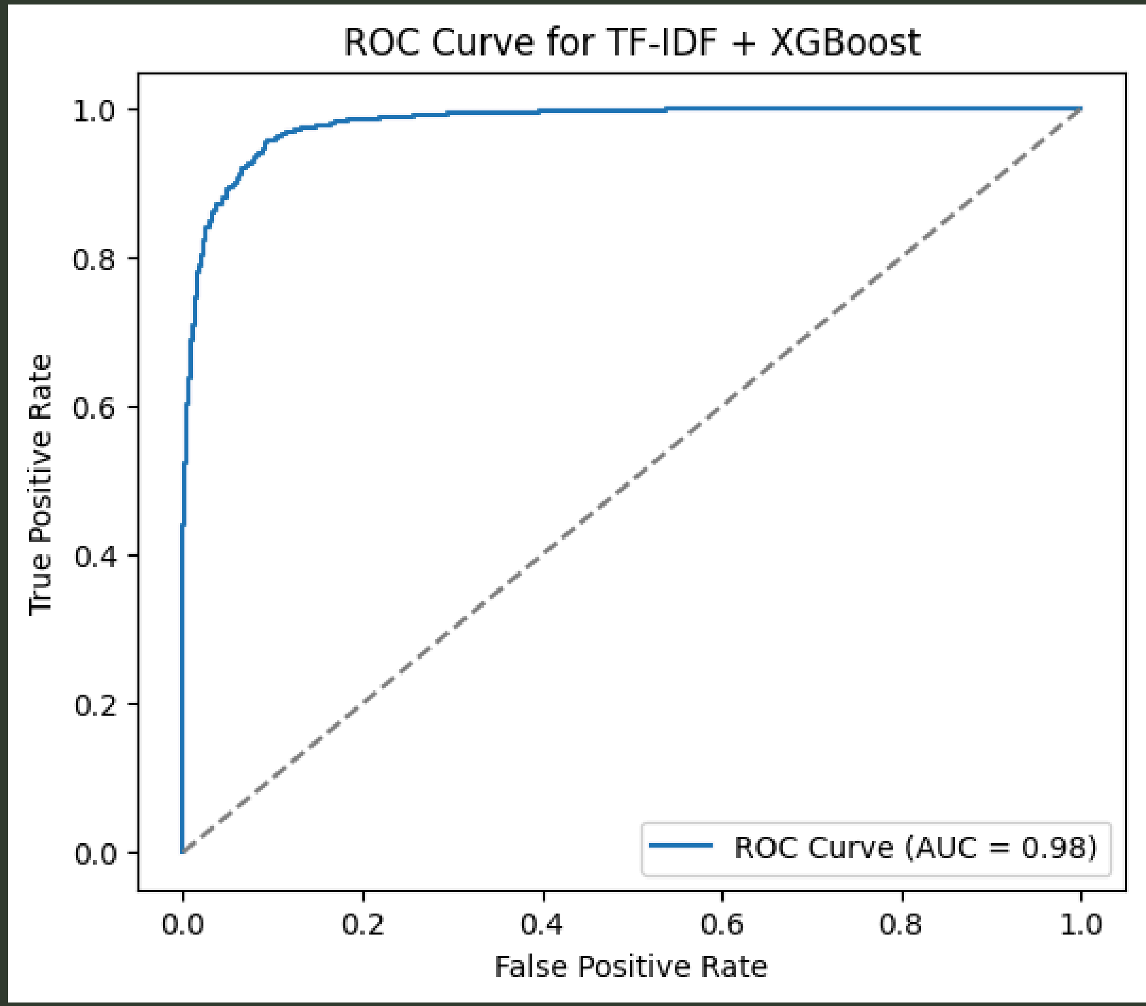
RESULTS

NLP + Model	Accuracy	True Label (1)			False Label (0)		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
TF-IDF + XGBoost	93%	92%	95%	93%	94%	91%	93%
TF-IDF + Naïve Bayes	91%	91%	91%	91%	90%	90%	90%
Bert + XGBoost	92%	92%	93%	93%	92%	91%	92%

RESULTS


ROC Curve for BERT + XGBoost
True Positive Rate
False Positive Rate
ROC Curve (AUC = 0.98)


ROC Curve for TF-IDF + Naive Bayes
True Positive Rate
False Positive Rate
ROC Curve (AUC = 0.97)


ROC Curve for TF-IDF + XGBoost
True Positive Rate
False Positive Rate
ROC Curve (AUC = 0.98)

CONCLUSION

- TF-IDF + XGBoost achieved the highest accuracy (93%), while BERT + XGBoost excelled in recall (92%-93%), both with strong ROC-AUC scores (0.98).

- TF-IDF + Naïve Bayes performed slightly lower (AUC 0.97, accuracy 91%), indicating its effectiveness but with room for improvement.

- Analysis of word usage, punctuation, and emojis highlighted patterns in fake news, reinforcing the need for robust detection models, with TF-IDF + XGBoost as the best scalable choice.

FUTURE WORKS

- Expanding datasets
- Integrate images, video, metadata
- Develop it as extension to test on articles
- Expanding to other area of news

References

[1] E. Essa, K. Omar, and A. Alqahtani, “Fake news detection based on a hybrid BERT and LightGBM models,” Complex Intell. Syst., vol. 9, no. 6, pp. 6581–6592, Dec. 2023, doi: 10.1007/s40747-023-01098-0.

[2] J. P. Haumahu, S. D. H. Permana, and Y. Yaddarabullah, “Fake news classification for Indonesian news using Extreme Gradient Boosting (XGBoost),” IOP Conf. Ser. Mater. Sci. Eng., vol. 1098, no. 5, p. 052081, Mar. 2021, doi: 10.1088/1757-899X/1098/5/052081.

[3] A. Nistor and E. Zadobrischi, “The Influence of Fake News on Social Media: Analysis and Verification of Web Content during the COVID-19 Pandemic by Advanced Machine Learning Methods and Natural Language Processing,” Sustainability, vol. 14, no. 17, p. 10466, Aug. 2022, doi: 10.3390/su141710466.

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[4] S. Girgis, E. Amer, and M. Gadallah, “Deep Learning Algorithms for Detecting Fake News in Online Text,” in 2018 13th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt: IEEE, Dec. 2018, pp. 93–97. doi: 10.1109/ICCES.2018.8639198.

[5] A. Jain and A. Kasbe, “Fake News Detection,” in 2018 IEEE International Students’ Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal: IEEE, Feb. 2018, pp. 1–5. doi: 10.1109/SCEECS.2018.8546944.

[6] N. Ruchansky, S. Seo, and Y. Liu, “CSI: A Hybrid Deep Model for Fake News Detection,” in Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, Singapore Singapore: ACM, Nov. 2017, pp. 797–806. doi: 10.1145/3132847.3132877.

Thank you!