Development of a Machine Learning-Based Model In Detecting Fake News: Analyzing Techniques For Accurate Content Verification

Esther Kinkosi Tomba[1*], Lawrence Mwenda Muriira[1], Timothy Anondo[1]

[1]*Kenya Methodist University P.O. Box 45240 – 00100, Nairobi, Kenya*

**Correspondence Email : tombaesther@gmail.com*

Abstract

Information through social media and other news outlets made detecting fake news crucial for individuals. The Pew Research Centre conducted surveys in the U.S.A to examine how adults consume news via social media, aiming to understand the behaviours and demographics of those relying on such platforms. This study addressed a critical gap in traditional fake news detection methods, which mainly used manual approaches and lacked advanced machine learning or AI techniques. Traditional methods are insufficient to handle the complexity, and contextual manipulation, where accurate information is presented misleadingly. To overcome these limitations, the study developed a ML Based model for detecting fake news, by analysing article content, and identifying patterns of misinformation. It employed advanced natural language processing techniques and supervised learning algorithms such as Decision Trees with 99.67% of accuracy, Logistic Regression with 99.13%, and Random Forest with 99.15%. Methods like Tokenization and TF-IDF were used to train the model using the ISO Fake news dataset. This dataset included real news from Reuters.com and fake news from unreliable sources flagged by PolitiFact and Wikipedia. Additional labelled datasets like LIAR and FakeNewsNet, along with newly gathered data, were used to supplement the training. Model performance was assessed using accuracy, precision, recall and F1-Score, all achieving 99.67%, demonstrating superior detection capabilities. The research contributed to ML by advancing NLP Techniques and improving fake news detection models. The study recommends future researchers, engineers and all those involved in developing machine learning systems to enhance further effectiveness should expand datasets and including diverse languages, applying deep learning models like RNN, CNN, and Transformers, (e.g., BERT, ROBERTa) for better contextual analysis, and establishing benchmarks using real-world case studies.

Keywords: *Machine Learning, Fake News Detection, Logistic Regression, Decision Tree, Randon Forest, ISOT Fake News dataset, Term Frequency, Inverse Document Frequency.*

IJPP 13(2); 28-41

1.0 Introduction

Digital media has fundamentally transformed how individuals consume and disseminate information. Worldwide, the rise of interactive platforms and internet-based news websites has become a primary source of news and real-time updates. However, this digital shift has also facilitated the rapid spread of fake news; intentionally false or misleading content that mimics legitimate journalism. The impact of such misinformation is profound: it influences political decision-making, incites social unrest, and tarnishes reputations on a global scale. As fake news grow more sophisticated, often spanning multiple modalities and languages, its detection becomes increasingly complex. Issues related to user privacy, real-time analysis, and cross-cultural interpretation complicate efforts to contain it. These global challenges call for the advancement of multimodal machine learning models and the deployment of real-time detection systems (Thakar & Bhatt, 2024). Recognizing the far-reaching implications, international organizations, governments, and research institutions have begun to address this issue with urgency (Villela et al., 2023).

Across regions, researchers are increasingly turning to machine learning (ML) as a scalable and efficient solution for fake news detection. Traditional methods largely reliant on manual content analysis are labour-intensive and slow. ML-based systems, in contrast, are capable of processing large datasets to uncover subtle patterns and indicators of falsehood that may elude human evaluators (Daud et al., 2023). ML models draw from diverse fields such as natural language processing (NLP), semantic analysis, and network analysis, offering powerful tools to detect and flag misleading content. Yet, current ML systems still face significant limitations. Many models lack the scalability and adaptability to keep up with evolving misinformation techniques (Wang, 2017), and some struggle to differentiate between credible journalism and nuanced misinformation, leading to false positives or undetected fake news (Su et al., 2024).

At the local or national level, the development of automated ML models is proving to be a critical strategy in combating misinformation. Studies using established datasets, such as the LIAR dataset by Wang (2017) which includes 12,836 manually labelled statements from the PolitiFact website serve as key benchmarks for evaluating detection accuracy. Various ML algorithms, including Support Vector Machines (SVM), Decision Trees, Logistic Regression, and Random Forest, have demonstrated strong performance in identifying deceptive content. For instance, ML-based detection systems have achieved accuracy rates as high as 94.21%, depending on the features and data quality used (Zahednejad et al., 2020c).

The growth of digital media and the widespread use of social media platforms have significantly increased the dissemination of fake news. The impact of such misinformation is profound: it influences political decision-making, incites social unrest, and tarnishes reputations on a global scale.

These models often utilize features such as linguistic cues, sentence structure, emotional tone, and word choice, effectively capturing complex feature interactions related to deceptive content (Pisner & Schnyer, 2019). Despite these advances, there remain critical challenges in accurately interpreting content in local contexts, including cultural references, timing of events, and the lack of real-time access to evolving facts. ML models can struggle in breaking news scenarios, where misinformation spreads quickly before verification occurs (Pandey et al., 2022).

The growth of digital media and the widespread use of social media platforms have significantly increased the dissemination of fake news, posing serious threats to public opinion, democratic processes, and social trust. There is an urgent need for advanced scalable and accurate approaches to automatically detect fake news. Leveraging machine learning and natural language processing techniques offers a promising solution (Kaliyar et al., 2021)

2.0Materials and methods

The study utilized a data frame consisting of observations of news articles for the purpose of training and evaluating, as well as implementing the ML model that only understands numbers. The research attempts to figure out how to convert texts into specific mathematical terms. Each row in the ISO Fake news dataset represent an individual news article. Tokenization of words extract meaningful features for a specific case use (Albahr & Albahar 2020). The aim was to determine whether an article contains fake news or not; hence, tokenization of words rather than sentences was considered since specific words in an article may highlight it as containing misinformation (Verma, et al., 2021). A vectorizer called TF-IDF measures the significance of a word in a document relative to a corpus of documents (Bahad et al., 2019).

Dataset

The model was trained using a vast and varied dataset. Training allowed to generate coherent and contextually relevant results. There were two files of ISO Fake news dataset obtained from ‘’realworld sources. The truthful articles were obtained by crawling articles from ‘’ Reuters.com’’ (News website) and fake news was obtained from unreliable websites flagged by Politifact (a fact-checking organization in the USA) and Wikipidia: one set for real news and another for fake news, both in English. The ISO Fake news was ranged between 2016 to 2017, at the University of Victoria in USA. After assessing the background, a total of 23,481 ‘’fake’’ tweets and 21,417’’real’ ’articles were considered. The research utilized a labeled dataset comprising news articles categorized as either valid or invalid. The dataset was structured in the two different classes: true and false. True: These are genuine articles; meaning they are accurate, truthful, and provide reliable information. This information helped establishing a baseline for detecting fake news. False: These are fake or fabricated news articles. A supervised classification for dataset labelled was significantly required. However, splitting of data involves dividing the dataset into subsets, which serve specific purposes like training and testing the model (Pardamean & Pardede, 2021). This step was crucial especially when evaluating model accuracy. Splitting data involves following steps: the TRANING-SET, and the TESTING-SET. The training-set comprised the majority of the data, accounting for up to 80% of the entire dataset. Testing-Set evaluated an end result of a trained ML model. Test set accounted for 20% of the entire dataset. The target indicating the numbers of entries in the dataset are classified as True and Fake is shown in Table 1.

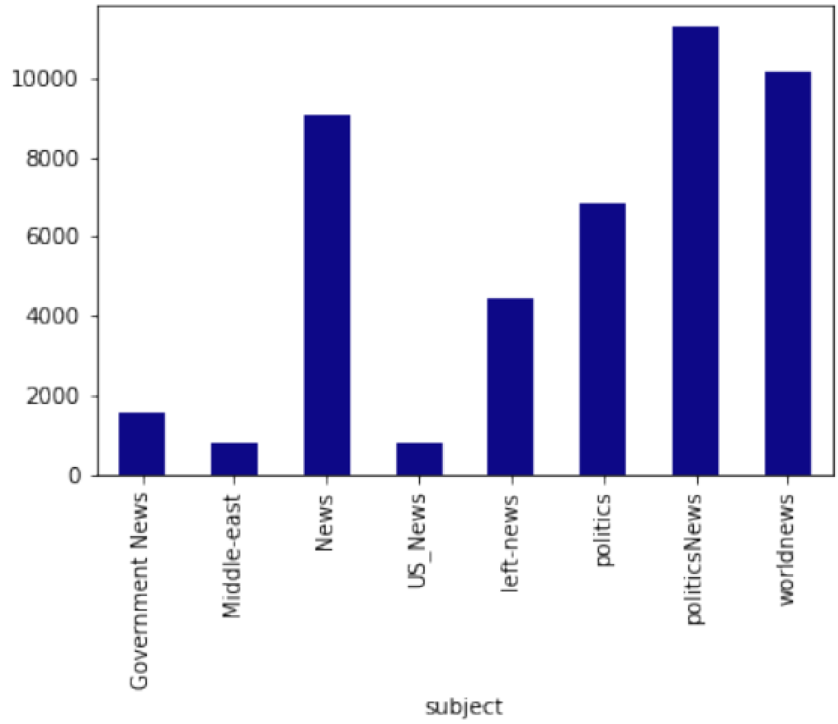
Table 1

ISOT Fake News Dataset

Target	Count	Percentage%
Fake	23,481	52.3%
True	21,417	47.7%

Figure 1

The ISOT Fake-News-Dataset: Bar chart showing count of articles per subject



Proposed model

Proposed model achieved an effective accuracies, precision, recall and F1score at 99.67%. It combines LG, DT, and RF to detect both fake and real news. Utilizing Logistic regression, confusion matrix analysis revealed the model correctly identified 4,238 fake news articles and 4,664 real news articles, with 45 false positives and 33 false negatives. While effective, its linear nature limited its ability to identify intricate patterns in the data. Decision Tree emerged as best-performing classifier, achieving an accuracy of 99.67%. It exhibited precision, recall, and F1 score values at 99.67% . This approach correctly classified 4,249 fake news articles and 4,701 real news articles, with only 8 false positives and 22 false negatives. Its ability to handle nonlinear relationships and hierarchical patterns in text data accounted for its superior performance. Moreover, the Random Forest model demonstrated high accuracy at 99.15%, with precision, recall, and F1 score values at 99.15%. It correctly identified 4,240 fake news articles and 4,664 real news articles, while generating 45 false positives and 31 false negatives. Although its ensemble nature improved robustness, it required more computational resources than the Decision Tree model (Mugdha et al., 2020).

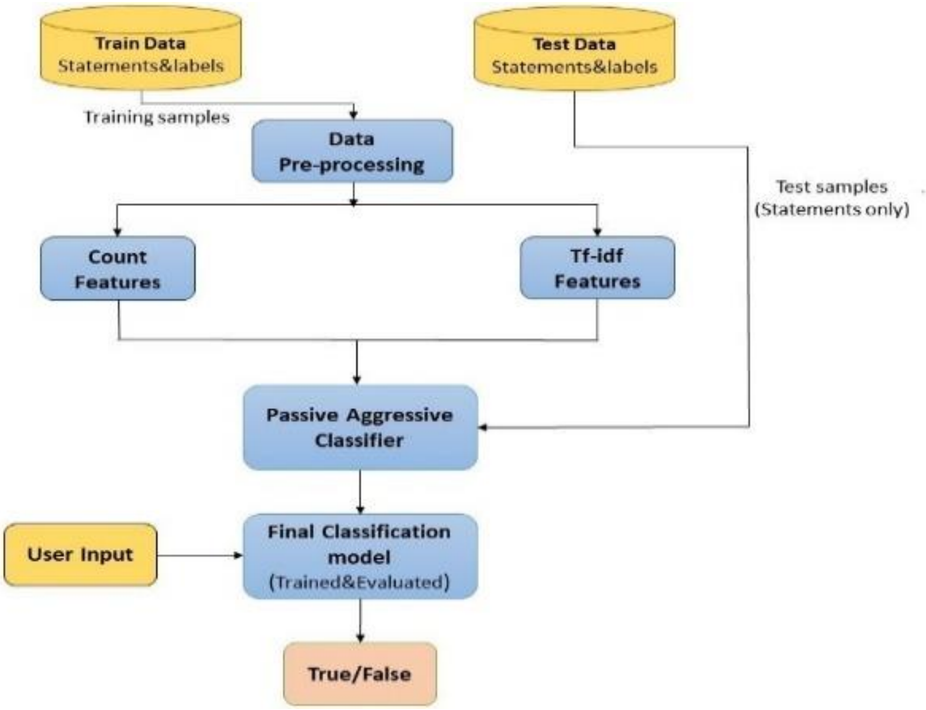
Model development

Building a model that can differentiate between fake news and real news, the study utilized a ML algorithms such as Natural Language Processing (NLP). This technique was selected because it could provide and perform good results than Computational Social Science Algorithms, such as Social Network Analysis (SNA), Temporal Analysis (TP), etc. for detecting fake news. Computational Social Science Algorithms examines and understands human or societal behaviors; whereas ML algorithms identifies patterns and anomalies in texts and images, including other data (Wang, 2017).

The architecture outlines a ML workflow for identifying fake news utilizing a Passive Aggressive Classifier. The pipeline is designed to fake news by altering text in numerical attributes, utilizing Count and TF-IDF, and training a Passive Aggressive Classifier for prediction. It supports real-time inputs from users (Nasir et al., 2021).

Figure 2

Architecture for model development



Data Preprocessing

In developing ML model, data preprocessing is an important step which enabled cleaning and preparing data, removing unwanted characters, noise or any HTML tags, and handling missing value (Cikambasi et al., 2024). Data cleaning is a critical part for building an effective fake news detection model. To remove unwanted characters and noise, unnecessary punctuation like ''question mark(?), comma (,), Semicolon (;)'', and special symbols such as @, #, etc. have been stripped out, which added no semantic value. Handling missing value enabled to manage incomplete or missing information within dataset.

Feature Selection

In this research, feature selection identified and selected relevant variables in a dataset which contribute to a predictive model's improvement. Irrelevant variables or features could degrade a model's predictive performance. The research used following machine learning algorithms: LG, RF, DT.

LR utilized binary and various class in classification tasks; while DT used tree-structure for decision making in selecting features (Ozbay & Alatas, 2019).

Feature Encoding

Encoding categorical variable or feature was significant in data processing, as many machine learning models work alongside numerical data like category variables. The study used two techniques for feature encoding: TF-IDF and Word Embeddings. TF-IDF was a statistical metric used to assess the significance of a word within a document in relation to a larger set of documents. It was used to transform text data within a matrix of TF-IDF attributes. Word Embeddings, such as Word2Vec were capable of capturing semantic connection between words (Pardamean & Pardede, 2021).

Feature Scaling

Sahoo's and Gupta's (2020) feature scaling is a method used to modify values of attributes, without distorting the differences in the ranges of values. However, in datasets, features have different units and ranges. For example, age may range from 0 to 100, etc. Therefore, unscaled data could lead to Biased Model Training, Inaccurate Distance Calculation, and Convergence Issues. Biased Model Training occurs when a machine learning model learns patterns that reflect imbalances, and unfair representations in the training data.

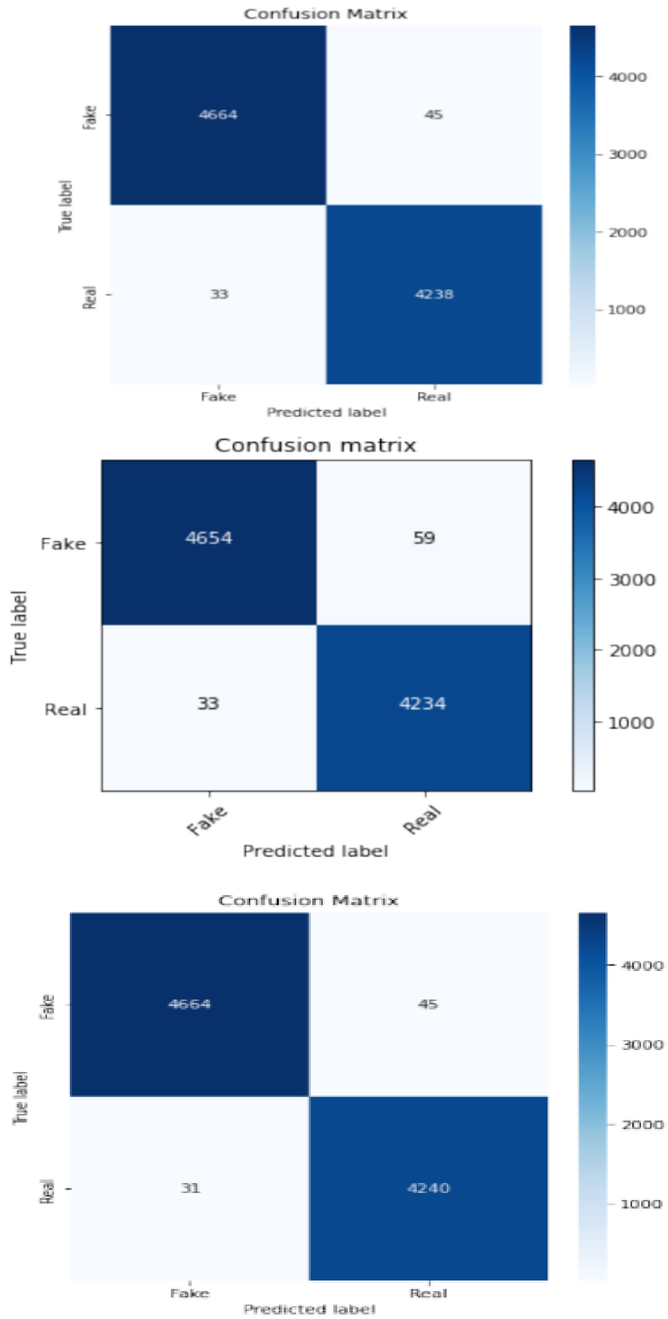
3.0 Results and discussion

Proposed model achieved an effective accuracy at 99.67%, compared to Taha et al. (2024b) at 98.5%, RF at 98.9% and DT at 99.4%; Oni et al. (2024) 99.64% of accuracy, RF at 99.23%, and LG at 98.80%; Al-Furaiji & Abdulkader (2024) 99% of accuracies, DT, RF, LG and SVM; Jain & Kasbe (2018) obtained 99.43% of accuracy, DT, RF at 98.75%, and LG 98.64%; Lyu & Lo (2020) performed at 92.4% accuracy and utilized DT with TF-IDF.

The creation of the fake news detection model depended on NLP methods to transform raw text data into valuable numerical representations. Among three classifiers evaluated, the Decision Tree model stood out due to its higher accuracy and efficiency of 99.67%, compared to Oni et al.(2024) 99.64% of accuracy; Unlike Logistic Regression with 99.13%, and Goldani et al. (2021) which achieved 99.8%, utilizing CNN, which is limited by its linear assumptions. The Decision Tree effectively captured nuanced and nonlinear patterns in the text. Compared to Random Forest with 99.13% (Birunda & Devi, 2021b) performed 99.5% using Gradient Boosting. Decision Tree offered similar levels of accuracy while being computationally more efficient, making it an ideal choice for practical deployment. The analysis of content verification approaches underscored the significance of method extracting features. TF-IDF proved to be an effective method for highlighting the relative importance of words, allowing the model to emphasize unique words and phrases that signal fake news (Pardamean & Pardede, 2021). This method enhance the classification accuracy of all models by refining the quality of input attributes. Techniques such as word clouds and frequency analysis played a significant role in identifying, distinguishing patterns in fake news and real news articles. For instance, fake news articles were characterized by sensationalist language and emotionally charged terms, whereas real news articles tended to use formal and factual language. Preprocessing steps like removing stopwords and punctuation further refined the dataset by eliminating extraneous elements that could have misled the models. The Decision Tree model exhibited outstanding performance in all evaluation metrics, attaining an accuracy, recall, precision and F1score at 99.67%. While Gereme et al. (2021) achieved 99%, the minimal occurrence of false positives and false negatives in the confusion matrix validated its effectiveness in differentiating between fake and real news. In contrast, Logistic Regression and Random Forest, while highly accurate, exhibited slightly higher false negative rates, which could reduce their effectiveness in applications where identifying fake news is critical, compared to Kaliyar et al. (2021) at 98.9% of accuracies.

Figure 3

Evaluation Metrics



Evaluation Metrics

The evaluation metrics, including Accuracy, precision, Recall and F1 score were used to assess the performance of the proposed model.

Accuracy

Accuracy was the primary evaluation metric for classification tasks. Helping to assess the proportion of correct predictions made by a model out of all predictions. The formula for accuracy was as follows:

$$\text{Accurancy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Where True positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are derived from the confusion matrix (Albahr & Albahar, 2020). The obtained accuracy of 99.67% indicates the proportion of total correct predictions. When compared with similar studies, for instance, Sanika et al. (April 2025), which reported an accuracy of 99.43% using Decision Tree, Logistic regression 98.64%, Random Forest 98.75%, the proposed model demonstrates competitive performance. These differences could be attributed to variations in ISO Fake news dataset quality. True positives(TP) occurred when both the actual and predicted labels were positive, representing the instances where the model correctly identified the positive class. On the other hand, true negatives refer to the instances where the model correctly predicted the negative class (Sahoo & Gupta, 2020). False negatives refer to the instances where the model mistakenly predicted the negative class, when actual label was positive.

Precision

Precision emphasizes the accuracy of positive prediction (Faustini & Covões, 2020).. It evaluates how many of the instances predicted as positive actually belong to the positive class. Precision also referred to the consistency of results, indicated by multiple measurements of the same thing giving similar results. Precision is associated with how method produces the same result under the same conditions. In other words, precision referred to the level of detail in numerical calculations, like the number of significant digits used in the value (Konkobo et al., 2020). Precision formula was as follows:

$$\text{precision} = \frac{TP}{TP+FP} \qquad (2)$$

Where TP refers to the number of true positive predictions, and FP denotes the number of false positives, Precision represents the proportion of positive predictions that are actually correct. A high prediction value indicates that the model is effective in minimizing false alarms, which is essential in applications where false positives carry significant consequences. In comparison, Oni et al.(2024) achieved high classification performance in their fake news detection study, using logistic regression and TF-IDF preprocessing, and reporting an overall accuracy of 99.64%. While precision was not separately reported in that study, high accuracy suggests correspondingly strong precision metrics. and minimal class imbalance. The precision obtained in our study complements the accuracy metric and confirms the model's capability in identifying relevant instances and minimizing incorrect positive classifications (Aslam et al., 2021).

From the formula above, True positives were instances correctly predicted positive, while False positives were those incorrectly predicted as positive. This metric became crucial when the cost of false positives was significant, such as in email spam detection. A researcher could avoid classifying legitimate emails as spam which are false positives (Pardamean & Pardede, 2021).

Recall

Recall, referred to as true positive rate, is a performance metric used to assess the effectiveness of a classification model, including its capability to identify all the relevant cases (Ahuja & Kumar, 2020).

$$\text{Recall} = \frac{TP}{(TP + FN)} \quad (3)$$

True positives refer to the number of positive instances correctly identified as positive, whereas false negatives represent the number of positive instances that are incorrectly classified as negative.

True positives(TP) denote true positives and FN false negatives. Recall measures the model's ability to correctly identify all actual positive instances. A high recall indicates that the model is effective at minimizing false negatives, which is crucial in domains such as fake news detection, which fails to detect harmful content. The recall also achieved 99.67%, indicating that the model was able to correctly identify a portion of the actual fake news articles.

When compared with a study by Jain & Kasbe (2018) who obtained 99.43%, using TF-IDF and logistic regression, a recall performance for the proposed model shows comparable effectiveness.

F1 - Score

F1 Score is a numeric used to assess performance of a classification model, particularly when there is an imbalance between classes. F1 Score helped to ensure that both positive and negative classes are considered.

$$\text{F1} - \text{Score} = 2 * \frac{Precission*recall}{precision+recall} \quad (4)$$

In this study, the F1-Score was computed to assess the balance between precision and recall. The obtained F1-Score of 99.67% reflects that the model achieves both high precision and high recall, indicating robust and balanced performance in detecting fake news. When comparing to the work of Mugdha et al., (2020) at 87% of accuracies, the inclusion of the F1-Score in the evaluation provides more comprehensive view of model performance, especially in binary classification problems where class imbalance could skew accuracy metrics.

Evaluation Metrics

The evaluation metrics table presents a comparative evaluation of three supervised machine learning algorithms, such as Logistic Regression (LG) at 99.13%, Decision Tree (DT) at 99.67%, and Random Forest (RF) at 99.15% based on their performance in detecting fake news. The assessment includes key classification metrics: Accuracy, Precision, Recall, and F1-Score, which provide insight into the model's effectiveness and balance between correctly identifying fake news and minimizing misclassifications. Therefore, Table 2 includes raw classification outcomes such as True Positives (TP) and True Negatives (TN), False Positives (FP), and False Negatives (FN), which underpin the metrics calculations (Almeida et al., 2021).

Table 2

Evaluation Metrics

Algorithm	Evaluation Metrics							
	Accuracy	Precision	Recall	F1Score	TP	TN	FP*	FN*
Logistic regression	99.13%	99.13%	99.13%	99.13%	4238	4664	45	33

Decision trees	99.67%	99.67%	99.67%	99.67%	4249	4701	8	22
Random forest	99.15%	99.15%	99.15%	99.15%	4240	4664	45	31

This evaluation metrics presented in Table 2 offers insight into the performance of the three machine learning algorithms LG. DT, RF in the task of fake news detection. The metrics include accuracy, precision, recall and F1-Score, each was supported by the confusion matrix elements such as True Positives(TP), True Negatives(TN), False Positives(FP), False Negatives(FN). Logistic-regression attained accuracies at 99.13%, while Birunda & Devi (2021b) achieved 91.5% utilizing BiLSTM with precisions, recalls, and F1-score all reaching 99.13% of accuracies. The confusion matrix has successfully identified 4,238 fake news articles and 4,664 real news articles, with 45 false positives and 33 false negatives. Although effective, its linear nature constrained its capacity, identifying more complex patterns in the data. A confusion matrix using heatmap illustrated in Figure 3 shows a clear representation of a classification of a model's performance. While Decision tree model proved to be top-performance classifier, reaching at 99.67% of accuracies, it demonstrated precision, recall, and F1-Score values of 99.67% across the board. It correctly classified 4,249 fake news articles and 4,701 real news articles, with only 8 false positives and 22 false negatives (Mugdha et al., 2020) at 87%. Its ability to handle nonlinear relationships and hierarchical patterns in text data accounted for its superior performance. Furthermore, Random-forest demonstrated high accuracy at 99.15%. It correctly identified 4,240 fake-news articles including 4,664 real-news articles, while generating 45 false positives and 31 false negatives. Although its ensemble nature improved robustness, it required more computational resources than DT model (Ahmed et al., 2020).

Model performance

Figure 4 presents a visual comparison of the performance of the three machine learning models LG, DT, and RF used for fake news detection. The performance metrics illustrated include Accuracy, Precision, Recall, and F1-Score, represented by distinct color-coded bars. As shown in Figure 4, the Decision Tree model labelled as the proposed model clearly demonstrates superior performance across all evaluation metrics, closely followed by Random Forest and Logistic Regression. This graphical representation reinforces the tabular results discussed earlier (see Table 2), where the Decision Tree model achieved the highest accuracy of 99.67% and exhibited the lowest false positive and false negative rates. The near identical height of the bars across metrics for each model indicates consistency in performance, however, the slight elevation in the Decision Tree's bars highlights its edge in classification effectiveness (Song et al., 2020). The figure provides an intuitive and immediate comparison that supports the recommendation of the Decision Tree as the most efficient and reliable model among them.

Figure 4

Model Performance

4.0 Conclusions

A basic data exploration was conducted to understand the distribution of articles per subject and the total number of articles. To gain more insights into the words used in fake and real news, word clouds was generated. For instance, from the dataset, the word clouds revealed that words like ‘’love’’, ‘’funniest’’, and ‘’bet’’ were more common in fake news, while words such as ‘’mossow’’, ‘’Reuters’’, and ‘’Russia’’ were more common in real news (Nasir et al., 2021).

The next step was the development of a model utilizing three methods: logistic regression, decision tree and random forest.

Assessment report showed, that the model carried out detection of both fake news and real news, achieving 99.67% in Accuracy, Precision, Recall and F1 score. Outcome matrix was created in demonstrating model results. It indicated that the system classified most of the real news as true and most of the fake news as fake. In addition to Logistic Regression, Decision tree was implemented in comparison with its performance including logistic regression. When comparing the three classifiers, both models performed extremely well. However, Decision tree classifier was more interpretable due its robustness.

5.0 Recommendations

Based on the study's results, recommendations could be made to enhance effectiveness of a ML model in detecting fake-news.

Future researchers, engineers and all those involved in developing machine learning systems for anomalies (fake articles as well) detection should first seek diverse data sources and extend the dataset. This includes fake news from diverse languages instead of focusing only in one language (English) by evaluating the performance of contexts. Second, utilizing deep-learning techniques: RNN(recurrent-neural-network), CNN (conventional-neural-networks), etc, transformers like BERT including ROBERT could improve contextual understanding. Third, there is need to establish benchmarks with day-to-day world case studies in assessing a model's success.

References

Ahuja, N., & Kumar, S. (2020). S-HAN: Hierarchical Attention Networks with Stacked Gated Recurrent Unit for Fake News Detection. *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 873–877. https://doi.org/10.1109/icrito48877.2020.9197914

Albahr, A., & Albahar, M. (2020). An Empirical Comparison of Fake News Detection using different Machine Learning Algorithms. *International Journal of Advanced Computer Science and Applications*, *11*(9). https://doi.org/10.14569/ijacsa.2020.0110917

Al-Furaiji, R. H., & Abdulkader, H. (2024). Comparison of the performance of six machine learning algorithms for fake news. *EAI Endorsed Transactions on AI and Robotics*, *3*. https://doi.org/10.4108/airo.4153

Aslam, N., Khan, I. U., Alotaibi, F. S., Aldaej, L. A., & Aldubaikil, A. K. (2021). Fake Detect: A deep learning ensemble model for fake news detection. *Complexity*, *2021*(1). https://doi.org/10.1155/2021/5557784

Bahad, P., Saxena, P., & Kamal, R. (2019). Fake News Detection using Bi-directional LSTM-Recurrent Neural Network. *Procedia Computer Science*, *165*, 74–82. https://doi.org/10.1016/j.procs.2020.01.072

Birunda, S. S., & Devi, R. K. (2021b). A Novel Score-Based Multi-Source Fake News Detection using Gradient Boosting Algorithm. *International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 406–414. https://doi.org/10.1109/icais50930.2021.9395896

Cikambasi, C. L., Muriira, L. M., & Murungi, R. M. (2024). Deep Learning Network Intrusion Detection with the Conv1d-Lstm Model: Integrating CNN and LSTM For Superior Performance. *International Journal of Professional Practice*, *12*(4), 41–49. https://doi.org/10.71274/ijpp.v12i4.475

Daud, S., Ullah, M., Rehman, A., Saba, T., Damaševičius, R., & Sattar, A. (2023). Topic Classification of online news articles using optimized machine learning models. *Computers*, *12*(1), 16. https://doi.org/10.3390/computers12010016

Faustini, P. H. A., & Covões, T. F. (2020). Fake news detection in multiple platforms and languages. *Expert Systems with Applications, 158*, 113503. https://doi.org/10.1016/j.eswa.2020.113503

Gereme, F., Zhu, W., Ayall, T., & Alemu, D. (2021). Combating fake news in “Low-Resource” languages: amharic fake news detection accompanied by resource crafting. *Information*, *12*(1), 20. https://doi.org/10.3390/info12010020

Goldani, M. H., Momtazi, S., & Safabakhsh, R. (2020). Detecting fake news with capsule neural networks. *Applied Soft Computing*, *101*, 106991. https://doi.org/10.1016/j.asoc.2020.106991

Jain, A., & Kasbe, A. (2018). Fake news detection. *2020 IEEE International Students’ Conference on Electrical,Electronics and Computer Science (SCEECS).*

https://doi.org/10.1109/sceecs.2018.8546944

Kaliyar, R. K., Goswami, A., & Narang, P. (2021). EchoFakeD: improving fake news detection in social media with an efficient deep neural network. *Neural Computing and Applications*, *33*(14), 8597–8613. https://doi.org/10.1007/s00521-020-05611-1

Konkobo, P. M., Zhang, R., Huang, S., Minoungou, T. T., Ouedraogo, J. A., & Li, L. (2020). A Deep Learning Model for Early Detection of Fake News on Social Media. *7th International Conference on Behavioural and Social Computing (BESC)*, 1–6. https://doi.org/10.1109/besc51023.2020.9348311

Lyu, S., & Lo, D. C. (2020). Fake news detection by decision tree. *SoutheastCon*. https://doi.org/10.1109/southeastcon44009.2020.9249688

Mugdha, S. B. S., Ferdous, S. M., & Fahmin, A. (2020). Evaluating Machine Learning Algorithms For Bengali Fake News Detection. *International Conference on Computer and Information Technology*, 1–6. https://doi.org/10.1109/iccit51783.2020.9392662

Nasir, J. A., Khan, O. S., & Varlamis, I. (2021). Fake news detection: A hybrid CNN-RNN based deep learning approach. *International Journal of Information Management Data Insights*, *1*(1), 100007. https://doi.org/10.1016/j.jjimei.2020.100007

Ozbay, F. A., & Alatas, B. (2019). A novel approach for detection of fake news on social media using metaheuristic optimization algorithms. *Elektronika Ir Elektrotechnika*, *25*(4), 62–67. https://doi.org/10.5755/j01.eie.25.4.23972

Pandey, S., Prabhakaran, S., Reddy, N. V. S., & Acharya, D. (2022). Fake News Detection from Online media using Machine learning Classifiers. *Journal of Physics Conference Series*, *2161*(1), 012027. https://doi.org/10.1088/1742-6596/2161/1/012027

Pardamean, A., & Pardede, H. F. (2021). Tuned bidirectional encoder representations from transformers for fake news detection. *Indonesian Journal of Electrical Engineering and Computer Science*, *22*(3), 1667. https://doi.org/10.11591/ijeecs.v22.i3.pp1667-1671

Sahoo, S. R., & Gupta, B. (2020). Multiple features based approach for automatic fake news detection on social networks using deep learning. *Applied Soft Computing*, *100*, 106983. https://doi.org/10.1016/j.asoc.2020.106983

Song, C., Ning, N., Zhang, Y., & Wu, B. (2020). A multimodal fake news detection model based on crossmodal attention residual and multichannel convolutional neural networks. *Information Processing & Management*, *58*(1), 102437. https://doi.org/10.1016/j.ipm.2020.102437

Pisner, D. A., & Schnyer, D. M. (2019). Support vector machine. In *Machine learning* (pp. 101–121). https://doi.org/10.1016/b978-0-12-815739-8.00006-7

Su, J., Cardie, C., & Nakov, P. (2024). Adapting fake news detection to the era of large language models. *Findings of the Association for Computational Linguistics: NAACL*

2022. https://doi.org/10.18653/v1/2024.findings-naacl.95

Taha, M. A., Jabar, H. D. A., & Mohammed, W. K. (2024b). Fake news detection model basing on machine learning algorithms. *Baghdad Science Journal*, *21*(8), 2771. https://doi.org/10.21123/bsj.2024.8710

Thakar, H., & Bhatt, B. (2024). Fake news detection: recent trends and challenges. *Social Network Analysis and Mining*, *14*(1). https://doi.org/10.1007/s13278-024-01344-4

Verma, P. K., Agrawal, P., Amorim, I., & Prodan, R. (2021). WELFAKE: Word embedding over Linguistic features for Fake News Detection. *IEEE Transactions on Computational Social Systems*, *8*(4), 881–893. https://doi.org/10.1109/tcss.2021.3068519

Villela, H. F., Corrêa, F., De Araújo Nery Ribeiro, J. S., Rabelo, A., & Carvalho, D. B. F. (2023). Fake news detection: a systematic literature review of machine learning algorithms and datasets. *Journal on Interactive Systems*, *14*(1), 47–58. https://doi.org/10.5753/jis.2023.3020

Wang, W. Y. (2017). "Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection. *Annual Meeting of the Association for Computational Linguistics*. https://doi.org/10.18653/v1/p17-2067

Zahednejad, B., Ke, L., & Li, J. (2020c). A novel Machine Learning-Based approach for security analysis of authentication and key agreement protocols. *Security and Communication Networks*, 2020, 1–15. https://doi.org/10.1155/2020/8848389