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Original Article

An Ensemble Machine Learning Approach for Reliable Fake News Detection on Social Media Platforms

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Abstract *- The high rates at which such misinformation is spread on social media platforms have further increased the need to have a strong and automated fake news detection system. This paper uses the Fake News Net dataset, which combines news and social characteristics, to offer a workable machine learning (ML)-based method for detecting bogus news. The first step in the methodology consists of a thorough text preprocessing, such as tokenization, lemmatization, noise, normalization of cases, and elimination of stop words, to ensure high-quality input to model training. After the cleaned dataset has been further divided into train and test subsets, the two classification models, Light Gradient Boosting Machine (Light GBM) and Decision Tree (DT), are used. Light GBM has been proven to be better as it can reliably deal with high volumes of textual data, potentially involving intricate patterns in context and is fast thanks to its scalable nature and leaf-wise tree growing approach. Experimental investigations show that Light GBM achieves an accuracy score of 86.02, outperforming the Decision Tree model and popular models like Random Forest and Naive Bayes. Furthermore, performance measurements including as accuracy, recall, F1-score, confusion matrices, and ROC curves confirm the reliability of the proposed technique. The comparative analysis justifies that Light GBM has a greater generalized and stable classification ability. All things considered, the essay presents a practical and successful method for identifying fake news, which raises the material's trustworthiness and stops false information from spreading on social media.*

Keywords *- Fake News Detection, social media, Machine Learning, Text Classification, ROC-AUC, Class Imbalance, Machine learning.*

1. Introduction

The advent of social media, for daily updates on events throughout the world, the general public mostly relies on internet news sources. Furthermore, there is no denying that the populace has access to these resources. However, because it provides unbiased and unedited news, traditional media has fallen behind in the competition to be the most popular website or to be the top site in order to provide the juiciest information [1]. The primary issue is that start-ups and smaller businesses are unable to pay editors to double-check or determine the veracity of any story. In order to make their own website the most popular one garnering all of the traffic, many social media sites also have a tendency to embellish the original news piece before releasing it [2][3]. Fake news originated as a result of these publications and inventiveness. Facebook, Google Plus, and other social media platforms are among the main places where bogus news is disseminated.

Social media is an environment that makes it possible to produce and distribute content quickly and affordably. Digital and Social media's vast distribution potential allows it to reach millions of individuals in a couple of minutes. Due to its growing popularity, social media has taken over as the primary information source for a large number of individuals globally. Despite these benefits, social media is regarded as a producing news medium that differs greatly from traditional news media [4]. As a result, their information is seen as being of inferior quality than that of the traditional news media. The distinction between information generation and news production is becoming increasingly hazy in digital media. It is vital to constantly assess the news that is shared on social media due to its low quality.

A composite machine learning (ML) method incorporates varied algorithms including decision trees, boosters, bagging solutions, and stacking frameworks to form a joint predictive framework. With such a mix of learners, the system is able to get the different sides of the coin about the data and thus more holistic when it comes to not being able to pick up deceptive patterns, which could have gone overlooked by an individual classifier [5]. This improves the accuracy of identifying fraudulent information, particularly with regard to the intricate, perplexing, and dynamic material on social media. Additionally, ensemble models provide a more thorough examination of news authenticity by accounting for language components like sentiment, grammar, and writing style as well as social context variables like user reputation and sharing behaviour. It is also necessary to construct an effective ensemble ML model for detecting false news on social media in order to protect digital ecosystems, promote public trust, and stop the harmful effects of disinformation [6][7]. With the digital environment constantly changing, establishing intelligent, adaptable, and scalable systems that can handle the proliferation of misleading information on the internet is thought to be caused by artificial intelligence (AI) and ML.

The paper is structured as follows: Section II reviews related work on fake news detection, Section III explains the process, including gathering data, pre-processing, and creating CNN models, Section IV presents results and comparative analysis, Section V concludes with important takeaways and suggestions for further investigation.

1.1. Motivation and Contribution

Social media's rapid expansion has changed how people obtain and share information, but it has also made it simpler for incorrect and misleading information to spread rapidly. The risks of fake news are tremendous because it can shape the opinion of people, disrupt the social harmony, and lack of trust in the credible information sources. The conventional manual fact-checking processes are too lengthy and resource consuming to respond to the amount and rate of online misinformation. This conundrum motivates the development of automated and data-driven techniques for accurately and successfully identifying false news. This paper presents an intelligent solution to this problem by utilizing machine learning models and well-organized datasets, like the Fake News Net seeks to lessen the dissemination of misleading information, assist in the early detection of fake information, and offer a safer online environment. This study's primary contributions are as follows:

- Presents a complete pipeline for detecting false news on the Fake News Net dataset, including social context and news content.
- Examine techniques for text preparation to enhance data quality and model interpretability.
- Offers a two-model based classification system of both Light GBM and Decision Tree as a better detection model.
- To guarantee reliable performance, the model was assessed utilizing the confusion matrix, F1-score, recall, accuracy, and precision.

2. Literature Review

This section discusses previous research on ML techniques for social media fake news detection. In Table I shows the methods, data, key findings and limitations of this study.

Kaliyar, Goswami and Narang (2019) Gradient descent techniques drive adaptive boosting classification approaches. This formulation supports important technique elements and parameters that optimize a single objective function. Multi-class datasets (FNCs) and machine learning models are utilized for classification experiments. Experimental data show that the ensemble framework outperforms benchmarks. Classified bogus news using four classifications using the Gradient Boosting method (an ensemble machine learning framework) with 86% accuracy [8].

Qawasmeh, Tawalbeh and Abdullah (2019) Neural network models perform better than conventional machine learning techniques because of their capacity for feature extraction. Still, there is a paucity of study effort on identifying false news in news and time crucial events. This article investigates the automated identification of bogus news on internet communication channels. Moreover, offer an automated identification of bogus news utilizing recent ML algorithms. The suggested model performs 85.3% accurately on the FNC-1 dataset using a bidirectional LSTM concatenated model [9].

Kareem and Awan (2019) Every area of life—politics, sports, business, entertainment, and much more—has fake news. It has shredded and constructed a corpus of 344 news items from well-known news websites, and manually labelled them as either true or false to identify fake news. There have been studies on two feature extraction methods: Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF). 7 different supervised ML classification methods were compared for their results. While K Nearest Neighbours (KNN), the top-performing classifier, achieves 70% accuracy, logistic regression only achieves 69% [10].

Hiramath and Deshpande (2019) proposed a technique for spotting false news, but the amount of data on social media and the internet is growing significantly these days, making it exceedingly challenging and time-consuming to determine whether or not news is accurate by examining all of the data. Therefore, categorize vast volumes of data using classification techniques. Here, suggested classification-based methods for detecting false news, include deep neural networks (DNN), logistic regression (LR), naïve bayes (NB), support vector machines (SVM), and random forests (RF) [11].

Helmstetter and Paulheim (2018) suggest a poorly supervised method that automatically generates a massive, but quite noisy, with hundreds of thousands of tweets in the training dataset. During collection, automatically categorize tweets according to their source, i.e., whether they originate from trustworthy or untrustworthy sources, then utilize this dataset to train a classifier. Then use that classifier to categorize tweets into false and non-fake categories, which is a new classification goal. Despite this flawed and inaccurate dataset, it shows that it can detect fake news with an F1 score of up to 0.9, even when the labels are inaccurate in accordance with the revised classification aim (not all tweets from an unreliable source need to be fake news, and vice versa) [12].

Girgis, Amer and Gadallah (2018) LSTMs and RNN method models (vanilla, GRU) are used to tackle the subject from a purely deep learning perspective in order to create a classifier that can identify whether or not a news article is fraudulent based just on its content. The LAIR dataset is used to illustrate the variations and results analysis. Despite the closeness of the results, the GRU is the best outcome, with a score of 0.217, followed by LSTM at 0.2166 and vanilla at 0.215. Considering these results, want to employ a hybrid model that attempts to improve accuracy by combining the GRU and CNN algorithms on the same dataset [13].

Della Vedova et al. (2018) In the context of social networks, ML techniques can be applied to accomplish this goal. Either content analysis which examines the news's substance or, more recently, social context models which map the news's distribution pattern are frequently at the heart of fake news detection techniques. This research first presents a novel ML method for identifying fake news that, by integrating social context information with news content, outperforms current methods in the literature by up to 4.8%. Second, apply the technique to a Facebook Messenger chatbot and evaluate it in a practical setting, attaining an 81.7% false news detection accuracy [14].

Table 1: Comparative Analyze Review of Fake News Detection Research

Author(s)	Methods	Dataset	Key Findings	Limitations & Future Work
Kaliyar, Goswami & Narang (2019)	Gradient Boosting (Ensemble ML), Gradient Descent–driven Adaptive Boosting	Multi-class FNC datasets	Ensemble framework achieved 86% accuracy, outperforming baseline models.	Limited to classical ML; future work could explore deeper architectures and richer linguistic features.
Qawasmeh, Tawalbeh & Abdullah (2019)	Bidirectional LSTM Concatenated Model	FNC-1 Dataset	Achieved 85.3% accuracy; neural networks outperform traditional ML models in feature extraction.	Lack of research on time-critical events; future work could incorporate temporal data streams and multimodal inputs.
Kareem & Awan (2019)	TF & TF-IDF with ML models (KNN, LR, etc.)	Manually constructed corpus (344 news items)	Best performance: KNN (70% accuracy) followed by LR (69%).	Small dataset size; requires larger corpus and deep learning approaches for better generalization.
Hiramath & Deshpande (2019)	ML Classifiers: LR, NB, SVM, RF, DNN	General web & social media data	Proposed a fake news detection mechanism to classify large-scale online data.	Performance metrics not reported; future work should include DL models and real-time detection pipelines.
Helmstetter & Paulheim (2018)	Weakly Supervised Learning; Automatic Labeling Based on Tweet Source	Large-scale noisy Twitter dataset	Achieved F1 score up to 0.9, even with imperfect labels.	Dataset is highly noisy; recommend refining labeling strategies and using semi-supervised or self-supervised learning.
Girgis, Amer & Gadallah (2018)	RNN Variants (Vanilla, GRU, LSTM)	LAIR Dataset	GRU outperformed LSTM and vanilla RNN by a little margin (score 0.217).	Accuracy remains low; future work includes hybrid CNN–GRU models for improved representation learning.
Della Vedova et al. (2018)	Content + Social Context ML Model; Hybrid Features	Social networks + Facebook environment	Improved accuracy by up to 4.8% over existing work; real-world chatbot achieved 81.7% accuracy.	Limited to Facebook; future scope involves cross-platform detection and advanced propagation modeling.

3. Methodology

The process of the Fake News Net dataset must be obtained in order to detect bogus news on social media networks and continues through a complete data preprocessing phase that involves tokenization, lemmatization, noise removal, lowercasing, and stop words elimination. To assess the model objectively, the dataset is preprocessed and then separated into subsets for testing and training. The proposed classification system then makes use of the Decision Tree (DT) and Light Gradient Boosting Machine (LGBM) models to differentiate between authentic and fake news. Finally, the system's performance is evaluated using metrics like F1-score, recall, accuracy, and precision. The findings show that the recommended approach is generally reliable. Figure 1 illustrate the flowchart of methodology.

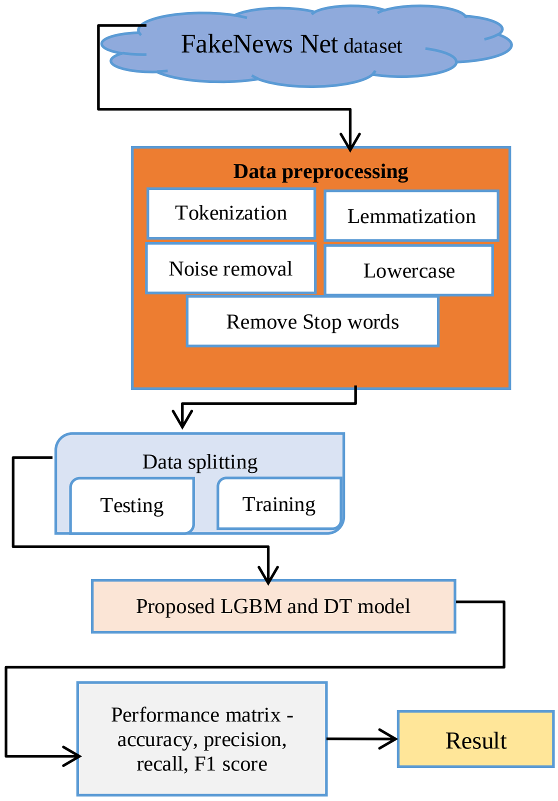

Fig 1: Flow Chart For Identifyingfake News Information On Social Media Platforms

These Fflowchart steps are discussed below

3.1. Data Collection

The dataset Fake News Net is a comprehensive resource that supports research on identifying using social context and news content together to spread misleading information on social media. It consists of detailed attributes of an article, like source, headline, main text, and multimedia (images or videos) attached, also user profiles on Twitter, posts, followers, and followers are provided.

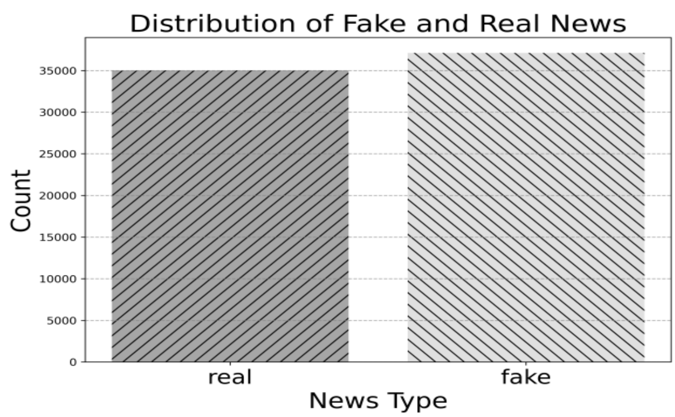

Fig 2: The Dataset Distribution

A relatively balanced dataset, with over 35,028 actual news pieces and a little over 37,106 Fake news articles, is depicted in the bar chart headed "Distribution of Fake and Real News" in Figure 2. Because it reduces bias towards the majority class and improves the dependability of assessment measures like accuracy, precision, and recall, Training ML models benefits from this balanced distribution, particularly when dealing with binary classification issues like fake news detection.

Fig 3: Word Cloud Of Fake News Articles

The word cloud in Figure 3 displays the most frequently used terms in the false news items; larger words are used more frequently. Such words as said, Trump, one and people are used quite extensively, so it seems that fake news material tends to be built around political personalities, utterances, and general assertions. The visualization assists in bringing out general topics and language patterns that are usually found in misleading or fabricated news.

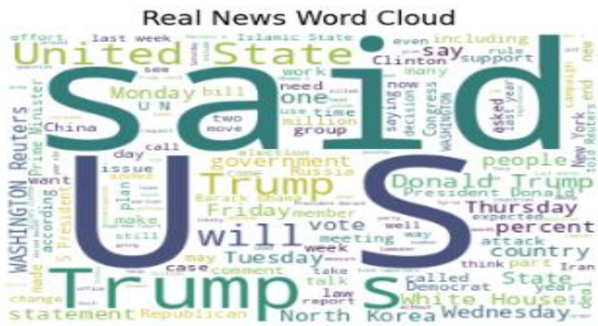

Fig 4: Word Cloud of Real News Articles

The most common words in real news articles are depicted in the word cloud, and the bigger the word, the more common it is used in Figure 4. The words that are used most frequently in the visualization include said, the U.S., Trump, state, and will, which indicate that the language applied when reporting real news is factual, event, and politically oriented. This symbolism allows bringing out the common words used in the context of plausible and confirmed news information.

3.2. Data Pre-processing

Before a model can correctly classify textual material, the text must be cleaned and pre-processed using a technique similar to the one outlined in the data-gathering step [15]. Before being transferred into ML models, it is necessary to pre-process the text data using techniques like case normalization, noise reduction, lemmatization, tokenization, and elimination. Several crucial procedures are used in this step to normalize and improve the text data, including:

- Tokenization: The natural text is divided into whitespace-free tokens in this stage. By breaking the text up into a set of constituent words, it is tokenised.
- Lemmatization: In order to obtain the term's fundamental form, the sufx must be removed or replaced in this phase. Additionally, it entails reducing the quantity of distinct occurrences of related phrases.
- Noise Removal: Eliminate extraneous characters, numbers, punctuation, email addresses, and links, among other items.
- Lowercase: Transform all terms and nouns to lowercase because they are identical. Training ML models is difficult since, in contrast, they consider "real" and "real" as distinct terms. To solve this problem, convert every letter to lowercase.
- Stop Word Removal: Stop words are grammatical elements of a text that aid in human comprehension but don't alter the meaning of the sentence. Examples of these are she, they, them, us, and so on. As a result, removing these stop words makes the learning feature set less challenging.

3.3. Data Splitting

In ML model training and evaluation, data splitting is the process of dividing the data into multiple subsets. Here, the data was split 80:20, meaning 80% was used for model training and 20% for performance testing.

3.4. Classification with Machine Learning Models
In this section, discuss the two ML models in below:

3.4.1. Light Gradient Boosting Machine (Light GBM)

The effectiveness of Light GBM, a high-performance gradient boosting system, in classification applications has attracted a lot of attention, particularly in domains involving large-scale and high-dimensional datasets, for example, spotting misleading material on social media [16]. In the context of this study, Light GBM is proposed as a core component of the ensemble model due to its scalability, speed, and ability to handle class imbalance and sparse input efficiently.

Light GBM builds decision trees sequentially in a leaf-wise manner with depth constraints, in contrast to the conventional level-wise method. Light GBM is able to preserve computational efficiency while achieving improved accuracy and reduced loss because to this leaf-wise growth technique. Each iteration of Light GBM tries to minimize the following objective function in Equation (1).

$$L^{(t)} = \sum_{i=0}^{n} l\left(y_i \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (1)$$

Where:
- L(t) is the t-th iteration's objectives function.
- l represents the loss function (for example, binary cross-entropy for classifying bogus news).
- yi the true label for instance.
- $\hat{y}_i^{(t-1)}$is the predicted value from the previous iteration
- $f_t(x_i)$ is the tree that was inserted at iteration t.
- $\Omega(f_t)$ is a regularization term that discourages overfitting by penalizing the model's complexity.

3.4.2. Decision Tree (DT)

A DT is a type of hierarchical structure that uses a variety of feature checks to create predictions. Let's call the decision tree DT, the input characteristics X, and the objective variable y. The decision tree separates the dataset iteratively based on feature tests in order to optimize class separation or decrease impurity. The forecast from the decision tree is shown in Equation (2):

$$DT(X) = \sum_{i=1}^{L} y_i \cdot I(X \in R_i) \quad (2)$$

The decision tree's leaf node count is denoted by L, the area or group of cases that the feature tests allocated to the i-th leaf node by R_i, and the class label assigned to the leaf node by y_i

3.4.3. Performance Metrics

In terms of detecting false news, to assess how well the detection methods work, many assessment criteria have been applied. In this work, the researcher puts attention on the most prevalent metrics and their approach to classifying false news and determining if an article is fraudulent:
- True Positive (TP): Shortly after they are anticipated, bogus news is interpreted as fraudulent broadcast fragments.
- True Negative (TN): Smithereens are considered factual news after the factual broadcast.
- False Negative (FN): Smithereens are seen as fake news following the anticipated real broadcast.
- False Positive (FP): Smithereens are mistaken for actual news shortly after their fake broadcasts.

Accuracy: The ratio of correctly identified examples (TP and TN) to the total number of predictions generated indicates how well the proposed ensemble ML model detects bogus news on social media sites. This may be mathematically expressed as Equation (3).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (3)$$

Precision: Precision may be calculated using the following Equation (4), which is the proportion of news items that are correctly detected as fraudulent of all individuals who are expected to commit fraud:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: Recall measures the model performance in determining real cases of fake news, and has mathematical form in Equation (5).

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1 Score: The accuracy and recall harmonic mean is the F1-score, a thorough measure of a model's ability to detect incorrect information. It is calculated in per Equation (6).

$$F1 - score = 2 * \frac{(precision*recall)}{(precision+recall)} \quad (6)$$

ROC: The efficacy of the classifier is measured by the ROC curve, a crucial assessment tool that displays the TPR (recall) versus the FPR under different threshold values.

5. Results and Discussion

The results of sentiment analysis in social media communications using Light GBM and Decision tree classifiers are shown in this section. All tests were conducted using Python, Windows 10 (64-bit), an Intel Core i5 CPU, and 8 GB of RAM. Table II provides a performance comparison of the Light GBM and the Decision Tree models on the Fake News Net dataset where Light GBM has higher metrics of 86.02% accuracy, 85.21% recall, 86.40% precision, and 85.23% F1 score compared to the 85.46% accuracy, 84.64% recall, 85.83% precision and 85.23% F1 score of Decision Tree model. These findings in support of Light GBM are its superior consistency and reliability in predicting fake news.

Table 2: Performance of Lightgbm Model on Fakenewsnet Dataset

Metric	LightGBM	Decision tree
Accuracy	86.02	85.46
Recall	85.21	84.64
Precision	86.40	85.83
F1-score	85.80	85.23

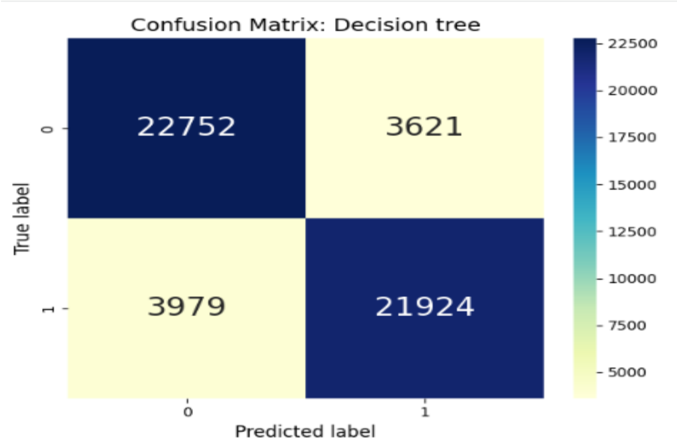

Fig 5: Confusion Matrix for DT Model

Figure 5 presents the confusion matrix of the DT model, in which it is possible to see the extent to which the classifier differentiates between two classes. The only false negative of the model that is properly identified is 22752 (0,0) and 21 924 (1,1) where the model is able to categorize real and fake statements. However, 3,621 class 0 are incorrectly labelled as class 1 (FP) and 3,979 class 1 as class 0 (FN), indicating areas where the model is weak with borderline.

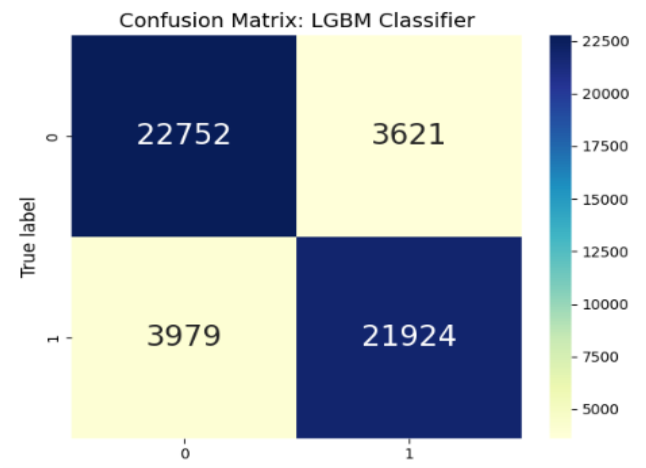

Fig 6: Confusion Matrix for Lightgbm Model

Figure 6 displays the Light GBM classifier's confusion matrix, and it shows how the classifier performs the task of differentiating between the two target classes. The model's 22,752 TN (0,0) and 21,924 TP (1,1) values demonstrate its accuracy in differentiating between genuine and false assertions. Meanwhile, Light GBM misses 3,621 and 3,979 occurrences of class 0 and 1, respectively (FP and FN).

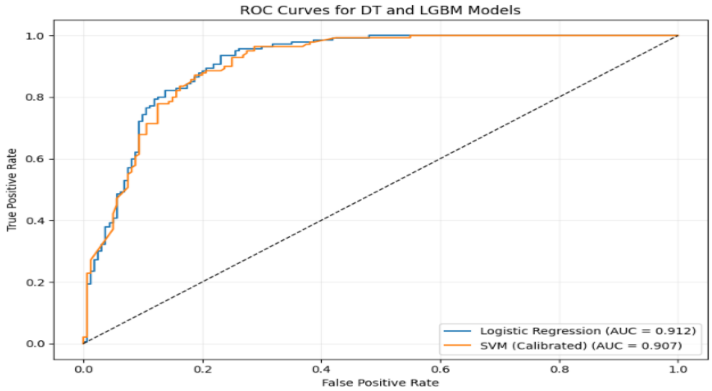

Fig 7: ROC Curve for DT and Light GBM Models

Figure 7 shows the ROC curves of the Decision Tree (DT) and Light GBM classifiers, with the two being able to differentiate between the two classes at different threshold values. The discriminatory performance between the two models is high, and the Light GBM has slightly higher AUC, which means that it has a better capability of classifying. The curves tend to increase sharply to the upper-left side, and it has low FPR and a high TPR. Light GBM curve is more consistent and smoother, whereas the DT curve has slightly fluctuating results, although it is also competitive.

5.1. Comparative Analysis

A comparison of Light GBM and Decision Tree are the suggested models for spotting misleading content on social media is shown in Table III. It is evident that Light GBM has the best accuracy of 86.02% and DT model closely at the second place with 85.46%. Conversely, the current NB captures a significantly lower accuracy of 70%, whereas the RF model has the lowest accuracy of 56.42%, which shows it is not effective in capturing subtle contextual matters. On balance, the given comparison indicates that the suggested Light GBM model is much more reliable and generalized, as compared to the classical text-based and probabilistic classifiers, which detect fake news in the social media.

Table 3: Comparison of Suggested and Current Algorithms for Social Media False News Detection

Metric	Accuracy
LightGBM	86.02
Decision tree	85.46
NB[17]	70
RF[18]	56.42

6. Conclusion and Future Scope

This study uses the Fake News Net dataset to propose a practical ML-based solution for detecting false information on social media platforms. After highly stringent pre-processing and the use of Light GBM and DT classifiers, the system was found to be highly efficient at distinguishing between authentic and fake news articles. Light GBM was also the most effective model in all assessed, being more accurate and precise than the DT and more traditional methods like NB and the RF and had superior recall and F1-score. The outcomes of the experimental conclusions highlight the significance of sophisticated gradient-boosting algorithm on high-dimensional textual data and the ability to capture small linguistic signs in the misinformation. On the whole, the given framework is a viable and efficient solution to suppress misinformation and provide more credible information distribution on the online space.

Future studies can examine the inclusion of DL models like Transformers or BERT-based models to obtain more substantial contextual and semantic contexts in news texts. Generalizing the model to multilingual or cross-platform news could also benefit it by increasing the level of generalization and robustness. Finally, one important area to focus on in practice is the development of deployment-friendly, lightweight models for real-time false news detection across social media platforms.

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