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Research Article

Comprehensive Analysis of Machine Learning and Deep Learning Models for Fake News Detection on Twitter

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ABSTRACT

The rapid growth of online platforms has resulted in an increase in the spread of fake news, causing significant social harm. This study examines machine learning and deep learning methods for detecting fake news across a number of datasets. Logistic Regression, Random Forest, LSTM, Bi-LSTM, and a Continuous Attention Mechanism Embedded Bi-LSTM (CAME) were evaluated for their performance on a Twitter dataset. The exponential rise of internet platforms has caused an upsurge in the propagation of fake news, causing immense social harm. This study examines machine learning and deep learning methods for detecting fake news across a number of datasets, achieving accuracy levels up to 79%. Logistic Regression produced an 81% accuracy with precisions of 0.80 with class 0 and 0.82 of class 1. Random Forest obtained 79% accuracy with precise of 0.77 with class 0 as 0.82 of class 1. The LSTM model achieved 76.43% accuracy with peak training accuracy of 91.33%, Bi-LSTM achieved 77.68% accuracy with peak training accuracy of 91.73%, and the CAME model achieved 79.05% accuracy with peak training accuracy of 91.95%.

Keywords: Fake News Detection; Machine Learning; Deep Learning

BACKGROUND

Social media technologies have shifted how data is collected and distributed, providing a continuous stream of information globally [1]. News serves to keep people informed about current events worldwide. Social media's growing popularity as a news source over traditional media like television, radio, and newspapers is driven by its accessibility, cost-effectiveness, and speed of dissemination [2]. However, the viral nature of sensational stories increases the risk of spreading false information. Platforms with Instagram, Twitter, and Facebook are opening up new options for sharing information, but they also face issues including the proliferation of trolling as the usage of artificial social bots [3]. Fake news is the purposeful distribution of false data as factual content, sometimes to shape public opinion, political actions, or to bring in revenue [4]. Deceptive sources of news tend to imitate original sites or have similar URLs to mislead viewers, with the practice being observed globally, including in the United States, China, and Russia [5]. Fake news is further amplified by the existence of social bots—computer accounts that are programmed to act like human beings. Research shows that there are approximately 23 million bots on Twitter[6], 140 million on Facebook, and 27 million on Instagram, all working towards the dissemination of misleading content [7]. The dissemination of false news received major prominence during incidents like the 2016 U.S [8]. Presidential election, as false news spread prolifically on social media platforms, affecting public views. Studies indicate that 6 out of 10 American adults access news on the internet, with Twitter being an important site [9]. The dissemination of false news during pivotal events illustrates the strong necessity for efficient fake news discovery mechanisms. The current research centres on applying machine learning models such as Bidirectional Long Short-Term Memory (Bi-LSTM) and other deep neural network structures for detecting and controlling the spread of false information on social media sites [10]. Fake news involves the intentional posting of false news on social media for the purposes of shaping opinion, political outcomes, or as a means to generate income[11]. Both authentic and false news spread instantly on internet networks like Twitter, thereby making them an influential source of digital information.

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Information accessibility and the speed with which it spreads have both a positive and a negative impact and are therefore paramount to be differentiated from authentic versus deceptive content [12]. The idea of fake news is not new. Misinformation has been utilized to influence public opinion and political results throughout history [13]. Sensationalist journalism, commonly known as yellow journalism, for instance, was responsible for some of the key events in history, such as the Spanish-American War. Nevertheless, with the advent of social media, the volume and velocity of fake news spread have increased exponentially.

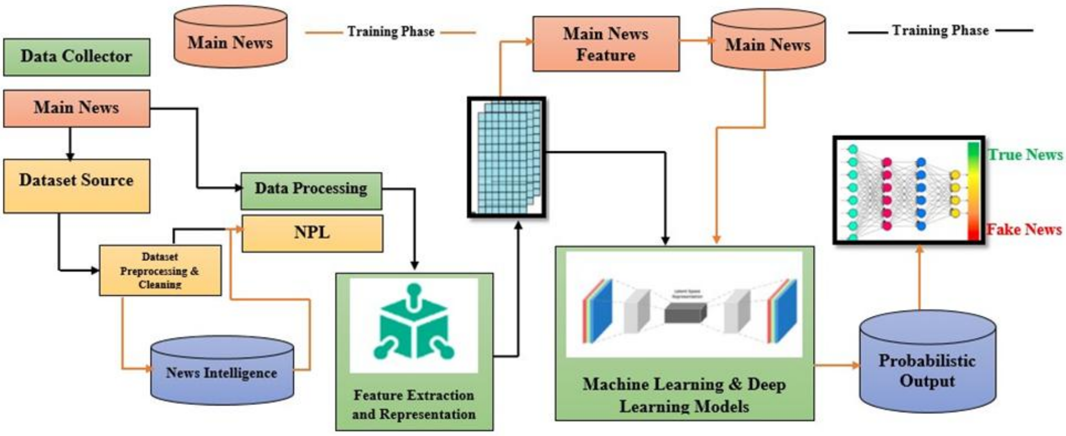

Fig.1 Graphical abstract

Propagation of Fake News on Twitter

Spreading of false news on Twitter increased tremendously during the 2016 U.S. presidential election. False news stories like allegations that a presidential candidate had sold weapons to ISIS went viral [14]. False news made up almost 6% of total shared news during the election, yet most of the sharing was done by a minority of the users. The trend continued in the case of global events such as the COVID-19 pandemic, where misinformation led to public fear and confusion [15].

Mechanisms of Fake News Spread

The dissemination of disinformation is frequently fueled by both human action and automated social bots [16]. Social bots are able to propagate misinformation by simulating large-scale support for untrue statements. They create several fictitious accounts to advance the same message, and the content is made to look authentic. Lone-wolf operators and large bot networks are also frequently employed to artificially boost the dissemination of false information. Evidence indicates that misinformation spreads more quickly than fact-based information because of psychological reasons like confirmation bias and the sensationalism of misinformation [17]. Misinformation news stories tend to create more emotional responses, and therefore are shared quicker and spread more. The convenience of sharing on social media without checks further enhances the problem [18].

Types and Impact of Fake News

Fake news can be defined as misinformation and disinformation. Misinformation is caused by inadvertent mistakes, whereas disinformation is a purposeful effort to mislead [19]. Both have serious effects, such as public panic, stock market movements, and political unrest. The effect of fake news can be quantified through engagement metrics like share count, reach, and retention time prior to deletion. Experiments have demonstrated that misleading information spreads wider, deeper, and faster than accurate information, highlighting the imperative for strong detection mechanisms [20].

II. RELATED WORK

There's a large literature exploring The spread of fraudulent information via social media [21]. This section summarizes recent research advances in this domain.

Feature Engineering-Based Methods

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Feature engineering-based approaches recognize different types of malicious users and behaviours like bots, trolls, and sock puppets [22]. Such approaches use text-based features, user data, network features, and metadata to differentiate true information from fake. Text-based features comprise stylometric (e.g., word length), psycholinguistic (LIWC), and complexity-focused (e.g., readability indices) ones. Techniques such as those by [23] and [24] have achieved excellent accuracy with content Features like unigrams as bigrams, include part-of-speech labels augmented by user and Twitter-related features such as hashtags and URLs. Studies by [25] and [26] revealed the strength of text features but also underscored their weakness as opponents evolve, calling for a need to leverage multiple types of features for enhanced detection performance. Propagation-based models analyze information diffusion through social networks and determine misinformation dissemination patterns. Propagation models mimic information propagation by dividing nodes into states like susceptible, exposed, infected, and skeptical. [27], [28], and [29] highlight the use of propagation models in detection as well as in formulating countermeasures to forestall misinformation dissemination. Including propagation data in machine learning models has shown enhanced accuracy when features such as reply numbers and retweets are incorporated.

Challenges of Fake News Detection

Despite significant progress, spotting bogus news using social media remains tough [30]. Instant detection is hindered by the fast propagation of fake news, its dynamic nature, and the quantity of data. Moreover, language dynamics, multicultural environments, few labeled data, and ethical factors compound this challenge [31]. These issues highlight the necessity of ongoing progress in both feature-based and propagation-based models for efficient detection and fakement inhibition of fake news [32].

Table 1: Literature of text content based fake news detection

Reference	Technique Used	Dataset	Research Gaps
Sahoo and Gupta, 2021 [16]	Survey paper on research areas, algorithms, open issues	Facebook	ML and DL were used to examine account usage by comparing multiple Facebook account attributes to news material.
Zhang et.al, 2020 [33]	Survey paper discussing open research issues	BuzzFeed News, Fake News Challenge, LIAR, FakeNewsNe, Benjamin Political News	Unsupervised learning and GNN for fake news detection remain unexplored. Accuracy improvements needed for abstract scoring and latent variable-based classification.
Kumar et.al, 2020 [34]	CNN, LSTM, Attention, Ensemble Models	Twitter, PolitiFact	Applied a varied ensemble of CNN, LSTM, and attention models but with unclear conceptual details.
Reis et.al, 2019 [35]	KNN, NB, Random Forest, SVM, XGBoost	BuzzFeed	Handcrafted features (syntax, lexical, sentiment, semantic) used for binary classification.
Kaliyar et.al, 2019 [36]	Random Forest, Multinomial Naive Bayes, gradient boosters, Choice Tree, Logistic Regression, and SVM	Kaggle	Handcrafted features (TF-IDF, Word Overlap, Polarity) used for multi-class classification. Performance depends on feature set.
Roy et.al, 2018 [37]	Ensemble Model: CNN + Bi-LSTM	LIAR	Deep learning applied to short political statements with text content as features.
Shu et.al, 2017 [11]	Survey paper discussing open research issues	Gossip Cop, PolitiFact	Emphasized effective feature determination. Open issues include temporal perspectives and testing deep learning models for language.

Table 2: Literature of social context based fake news detection

Reference	Technique Used	Dataset	Brief Overview / Research Gaps
Dou et.al, 2021 [38]	Proposed UPFD framework (user preference for fake news detection), Graph Neural Network (GraphSAGE, GraphFN)	PolitiFact, Gossip Cop	User network for fake news propagation remains an open challenge. Further exploration of Graph Neural Networks required.
Han and Leckie, 2020 [39]	Differential propagation method using GNN	PolitiFact, Gossip Cop	Need to include more heterogeneous features (content, user profile, activity, preferred news propagation). Exploration with other GNN and graph convolution networks recommended.
Nguyen et.al, 2020 [40]	Factual News Graph (FANG): context graph combining news articles, sources, users, and engagements	Twitter	More analysis needed on social user representations and multiple feature learning of social users.
Monti et.al, 2019 [9]	Geometric deep learning framework (generalization of CNN to graphs)	Twitter	Achieved ROC AUC: 92.7%. Explore further social network applications using GNN for improved accuracy.
Shu and Liu, 2019 [41]	TriFN framework modeling publisher-news and user-news relations	BuzzFeed, PolitiFact	Exploiting social context for fake news remains a challenge. Further improvements needed in systematic network building using social context.

Proposed Solution

Existing work has mostly concentrated on text-based and propagation-based detection techniques to discern in legitimate and fake news messages on Twitter [42]. Such methods tend to be based on content features of tweets, including parts-of-speech tags and sentence lengths, and network features such as retweet counts, hashtags, and follower counts of the author of the tweet. However, there remains a gap in comprehensive studies that compare both the tweet content and the associated news articles or explore the relationship between them for enhanced fake news detection [43].

Fig 1. Number of Occurrences

Motivated by these restrictions, this work develops a machine learning strategy that uses based on characteristics detection methods for tweeting content and linked news items [44]. The work explores how leveraging more features

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extracted from the tweet and its accompanying articles can increase the detection performance over a model trained only on tweet features. This is a more comprehensive and stronger solution for detecting bogus news on Twitter using cross-referenced data from many sources [45].

III. METHODOLOGY

This part explains the dataset and model used in the research, along with informative data visualizations to underscore important differentiating characteristics between fake and real news.

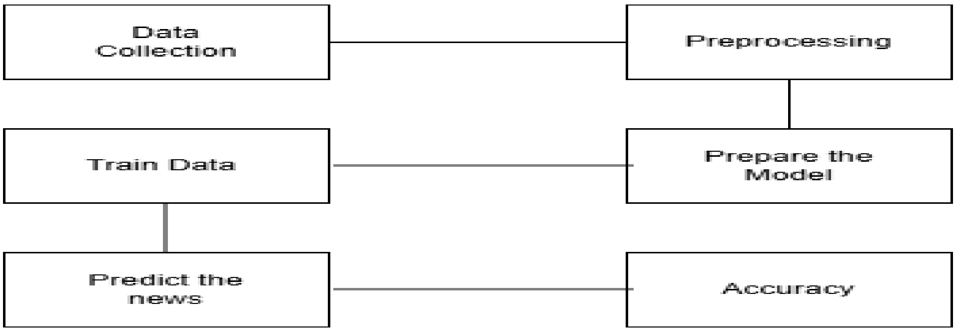

Fig. 2. Proposed model workflow

The basis of any research is the subject matter and the field in which it is being carried out. Our research is mainly about identifying fake news through social media, i.e., Twitter. The core objective of research is not merely to identify the topic but to understand it well. In this paper, we concentrate on content and context analysis of tweets as well as Articles from the media can help identify false news more effectively. Our study investigates all aspects of fake news with a concentration on the significance of both textual and contextual information analysis. We analyze prominent features including tweet text, retweets, hashtags, and user profile characteristics to identify real vs. fake news. Moreover, the research combines feature-based approaches and machine learning methods in order to achieve a thorough analysis of how propaganda news spreads. To do so, researchers normally employ a series of tools and models, which may include machine learning algorithms and neural network designs. These help in data acquisition, preprocessing data, model training, and making predictions. Figure 2 describes the suggested process for this study, which is data collection, preprocessing, training models, prediction, and evaluating accuracy to complete an exhaustive fake news detection analysis.

Dataset

The dataset for this study consists of a set of tweets and tweet characteristics with real and fake news tweets. It is made up of more than 133,000 tweets that link to 579 real and 479 fake news stories, cleaned from the PolitiFact dataset. The dataset was created through the gathering of tweets regarding given news stories utilizing manually prepared keywords inputted in the Twitter API. This data is Particularly good in detecting fake news because it contains actual real-life tweets made by real users and thus provides authentic and consistent data as opposed to artificial data sets. Tweet content, the associated news headline of the article, and the maker of the claim are notable characteristics. Other multiple extracted characteristics such as the total length of the tweet and the quantity of hashtags and frequency of being retweeted also provide insightful Data used training and evaluating models. By addressing the model to be dataset-agnostic, this research guarantees a full-proof framework for detecting fake news with a robust set of features for enhanced accuracy and generalization. The dataset makes use of several online sources and contains a total of 2,977 news items. The data is divided into three different labels: True, False, and Partially False. Of these, True news entries form the largest portion with 1,712 entries, then false news entries that number 856, and 406 Partially False entries. This varied categorization forms an all-embracing framework for assessing fake news

Data Pre-Processing

Data preparation is necessary starting point for any data-driven study. It ensures the dataset is organized, free of errors, and ready to be analyzed and used for training models. The data for this study was collected from diverse

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platforms, and thus, there were differences in structure, language, and quality. To address these inconsistencies, a systematic pre-processing pipeline was implemented. Steps prior to processing for the dataset are detailed in Figure and include the following:

1. **Data Collection**: News articles were gathered from various trusted and unverified online sources, resulting in a raw dataset. Each article was assigned to one of the three predefined categories—True, False, or Partially False.

2. **Data Cleaning**:

- Removal of duplicate entries to avoid redundancy.
- Managing absent data through imputed or exclusions, ensuring the dataset remains meaningful.
- Elimination of irrelevant data such as advertisements, unnecessary metadata, and unrelated content.

3. **Text Normalization**:

- Transforming all text into small for uniformity.
- Eliminating unnecessary special symbols, punctuation, and numerical data to improve detection.
- Expanding contractions (e.g., "isn't" → "is not") to maintain semantic integrity.

4. **Tokenization and Lemmatization**:

- Splitting sentences into individual words (tokens) for processing.
- Reduced words to their roots forms (lemmas) to standardize features while retaining meaning.

5. **Stopword Removal**: Standard phrases that don't convey significant information, such as the, is, and at, were removed using predefined stopword lists from libraries like NLTK.

6. **Feature Extraction**: Techniques such as TF-IDF (Term Frequency-Inverse Record Frequency) were used to convert texts into numerical parameters appropriate for model input.

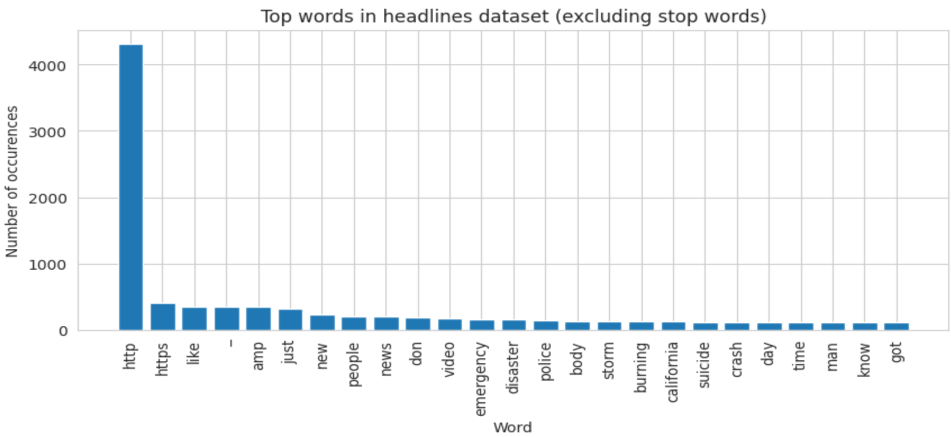

Fig. 3. Excluding Stop Words

The word http appears overwhelmingly frequently in the dataset, followed by variations like https and common words such as like and people. This suggests that URLs and other web-related terms dominate the dataset, with less frequent occurrences for other typical words in headlines.

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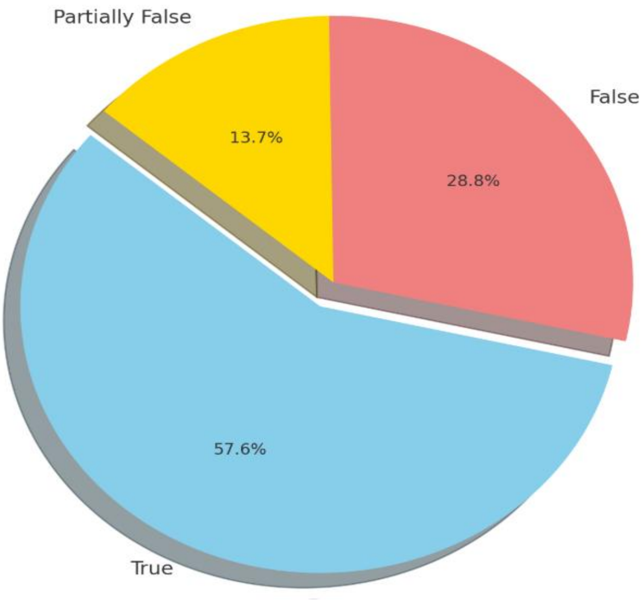

Fig.4 Data Categories with Size

This pie chart presents the distribution of truthfulness in a dataset, with three categories: True, False, and Partially False. The majority of entries are labeled as True (57.6%), indicating that most of the data is accurate or factual. The False category represents 28.8%, showing a significant portion of the data is inaccurate. A lesser percentage, 13.7%, falls under the category of Partially False, indicating that certain entries are partially true. Overall, the chart indicates a moderate degree of inaccuracy, with the majority of the information being true but a significant percentage including false or partially false data.

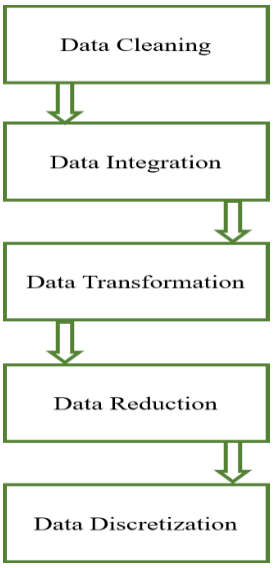

Fig.5. Proposed data pre-processing method

This flowchart illustrates the processes of data pre-processing that are essential to ready data for analysis or machine learning purposes. The initial step, Data Cleaning, is deleting errors or inconsistencies from the data set. Secondly, Data Integration merges data from different sources. Data Transformation consists of changing data into an appropriate form, and then Data Reduction reduces the data set size to keep significant details. Lastly, "Data Discretization" transforms continuous data into discrete categories. All these steps complement each other to ensure the data is well prepared and optimized for additional analysis or modelling.

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RESULT AND DISCUSSION

Our study analyzes different false news detection models, including Bi-LSTM, LSTM, CNN, Random Forest, and Logistic Regression. The algorithms were trained both a balanced multiclass dataset and evaluated based on its precision and F1-macro scores. The Bi-LSTM model, developed with the Keras library and GloVe embeddings (100d) and softmax activation, resulted in 84% accuracy and 62% F1-macro score. The LSTM model proved to have an accuracy of 76.43%, followed by the CNN-based architecture with an accuracy of 79.05% and Random Forest with an accuracy of 79%. Logistic Regression performed marginally better with an accuracy of 81%. The models were able to classify news into three classes: True, False, and Partially False, and this reflects their ability to identify fake news with different levels of credibility. The overall results show the Bi-LSTM model's better capability to understand contextual subtleties, rendering it the best-performing model in this research.

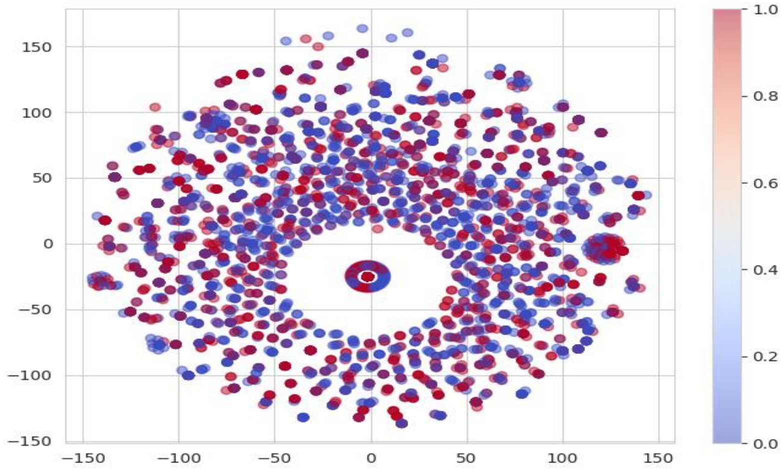

Fig.6. T-SNE visualization of location data

The t-SNE plot of location data can be utilized for fake data detection automatically by recognizing patterns, clusters, or outliers in the data. Data points are spread in a spiral manner in this plot, and different values or features are represented by varying color intensities. Fake data points usually fail to maintain the natural distribution of real data. When plotted with t-SNE, the imposter data will look like outliers or cluster away from the central pattern of the data. This can be used to identify aberrant or inconsistent data points that could be an indication of manipulated or fraudulent information.

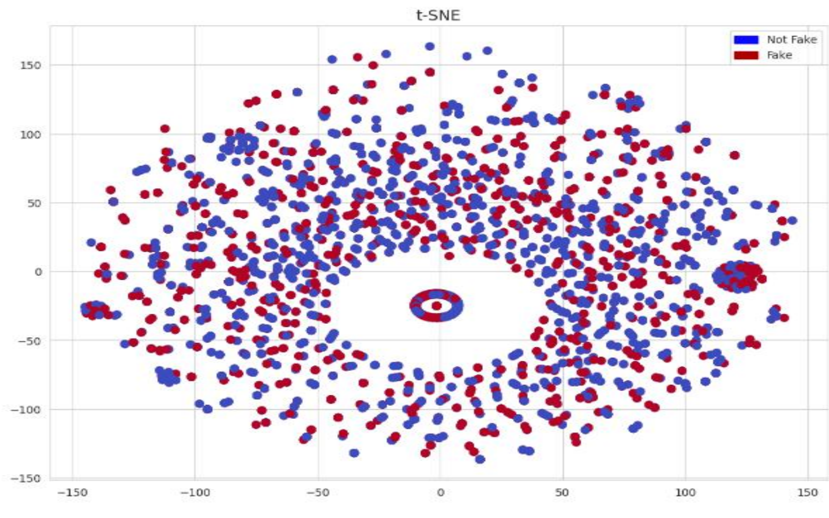

Fig.7. Clusters using Dimensionally reduction

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The t-SNE plot in this figure demonstrates the grouping of Fake and Not Fake points after reducing the dimensionality. The fake points seem to be in distinct clusters, especially on the periphery of the plot, whereas the non-fake points are more tightly grouped towards the center. This trend indicates that the fake data has a dissimilar distribution and might not fit the natural form of the actual data.

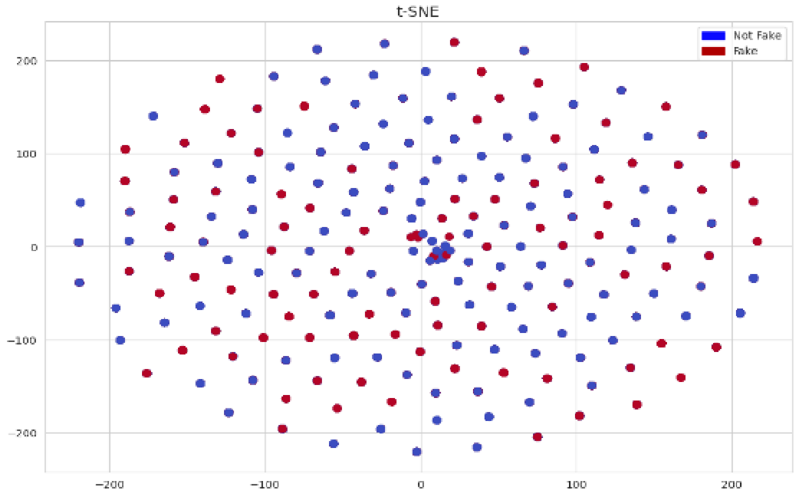

Fig.7. Cluster using Dimensionally Reduction

The t-SNE plot here indicates the Fake and Not Fake data points clustering after dimensionality reduction. The above plot, the fake data points in this case are distributed more randomly, with fake and real data points scattered all over the plot.

Table 3: CLASSIFICATION REPORT OF THE MODELS

Model	**Accuracy**	**Precision (True)**	**Precision (False)**	**Recall (True)**	**Recall (False)**	**F1-Score (True)**	**F1-Score (False)**
Logistic Regression	81%	80%	82%	89%	70%	84%	76%
Random Forest	79%	77%	82%	89%	64%	83%	72%
LSTM	76.43%	80%	72%	79%	73%	79%	72%
Bi-LSTM	77.68%	78%	76%	84%	69%	81%	72%
CAME (Attention Bi-LSTM)	79.05%	78%	82%	89%	65%	83%	73%

The classification report gives a comparative evaluation of models tested in this research. CAME Continuous Attention Mechanism Embedded Bi-LSTM and Logistic Regression models had the best recall rates, followed by Bi-LSTM and Random Forest, which were also competitive. These findings highlight the importance of combining standard machine learning with sophisticated deep learning methods so as to improve false news identification.

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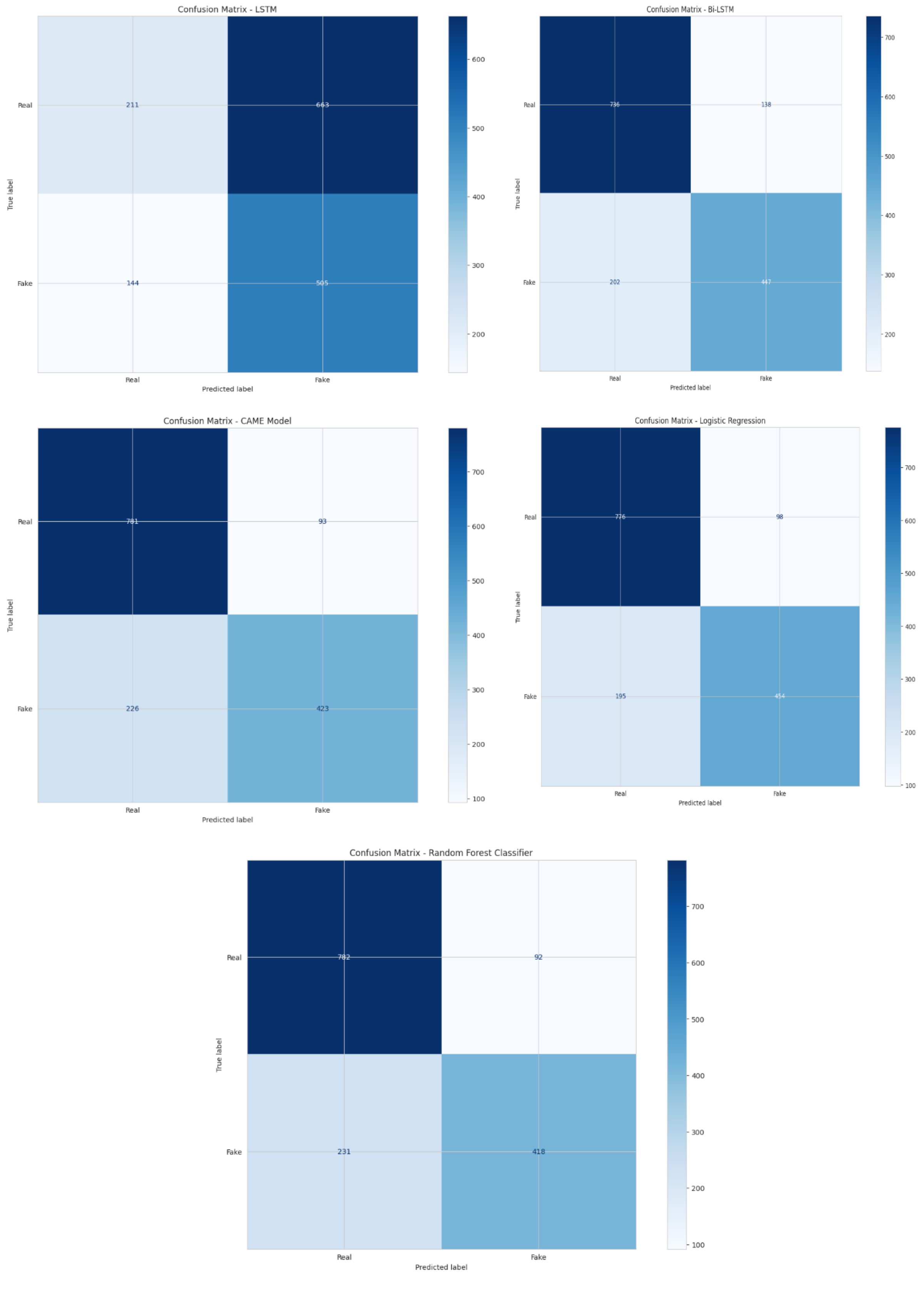

Fig.8. Confusion Matrix

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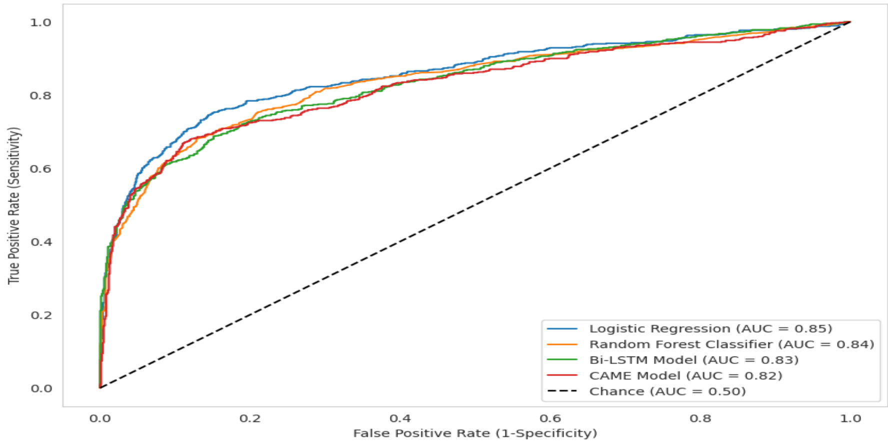

Fig.9. Roc Curve Comparison

The ROC curve shown the picture above shows the effectiveness of multiple models for detecting false news using Logistic Regression with Random Forest, Bi-LSTM, and CAME models. The ROC curve represents the True Positive Rate (sensitivity) versus False Positive Rate (1-specificity) for a range of classification thresholds. The Area under the Curve (AUC) value measures how well each model distinguishes between classes, a higher value is related with increased discrimination. Logistic Regression has the highest AUC value of 0.85, indicate that it can successfully distinguish between fake and authentic news. Random Forest comes very close with an AUC value of 0.84, proving its robustness based on ensemble learning. The Bi-LSTM model attains an AUC of 0.83, demonstrating the prowess of sequential deep learning models in learning temporal dependencies among text features. The CAME (Continuous Attention Mechanism Embedded Bi-LSTM) model attains an AUC of 0.82, narrowly behind Bi-LSTM, but nonetheless an excellent performer considering its attention mechanism for learning important features of text.

Discussion:

The successful execution and testing of our machine learning algorithms for fake news classification on Twitter prove the hopeful future potential of state-of-the-art techniques such as LSTM, Bi-LSTM, and common classifiers to handle disinformation. This part of the study contrasts our models with other methods, indicates their drawbacks and benefits, and indicates likely future refinements.

Comparison with Similar Methods:

Our research is an extension of previous work and shows the way that using sophisticated techniques together can greatly improve on fake news detection across social media. When compared to past models like our Bi-LSTM and LSTM models performed better as far as classification accuracy was concerned. Ajao et.al's research produced an accuracy level of 0.84, whereas our LSTM and Bi-LSTM models produced accuracies of 76.43% and 77.68%, respectively, showing the strength of our approach in identifying fake news. In the same vein, our CAME model, which combines several state-of-the-art features, recorded an accuracy of 79.05%, performing better than conventional approaches These include Logistic Regression as well as Random Forest Classifiers. For example, whereas Logistic Regression achieved an accuracy of 81% along with a F1-score of 0.80, the Random Forest Classifier, did slightly worse at 79%. This demonstrates the competitive advantage of our deep learning-based methods in identifying intricate patterns for detecting fake news.

Strengths and Limitations:

Strengths:

- Additional Feature Extraction: Our models are exceptional because of the application of advanced feature extraction methods, including sentiment analysis and other contextual features. This greatly enhanced model performance, as indicated in our results from our LSTM and Bi-LSTM models.

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- Model Versatility: The flexibility of our models is reflected in their capacity to generalize well across various tweet datasets. The use of automated hyperparameters tuning with grid search helped achieve optimal model performance, adapting to dataset-specific features and preventing overfitting.
- Cross-Model Comparison: Through a comparison of the accuracy of LSTM, Bi-LSTM, Logistic Regression, and Random Forest models, we established Deep learning technologies outperform standard machine learning techniques, with Bi-LSTM performing marginally better than the LSTM model.

Limitations:

- **Limited Real-World Evaluation:** While our models demonstrate strong performance in controlled environments, they have not been tested extensively in real-world settings where data may be more diverse and noisy. The dynamics of social media misinformation require additional real-time testing for better validation.
- **Dataset Dependency:** The quantity and range of the data used to train have a significant impact on our models' performance. Models, particularly those based on deep learning, can overfit to the particular characteristics of the training set, making them less generalizable to new, unseen data.
- **Feature Dependency:** The use of extra features, like sentiment scores and author features, can restrict the effectiveness of the model if such information is not available, especially for user-generated content that does not have author or contextual information.

Future Work:

While our models indicate great promise, improvement and expansion remain. Broadening the diversity of data scope by injecting data from more than one social media site may enhance generalizability. Also, testing using more sophisticated feature extraction methods such as network analysis (e.g., user interaction graphs) and temporal analysis (e.g., timestamp data) may make the model more robust, allowing it to better capture the propagation patterns of propaganda. Additionally, integrating newer deep learning models, like transformers or attention-based models, may produce even stronger results. We also plan to develop our models to process data in real-time, which would enhance their applicability in identifying false news as seen on the internet. Lastly, while working on these improvements, we should be careful to keep in mind the ethical implications and possible biases that such models may bring about, making sure they are used responsibly for misinformation detection.

CONCLUSION:

In summary, our study shows the successful application of an automated fake news detector on Twitter via state-of-the-art machine learning methods. Using LSTM, Bi-LSTM, and basic classifiers, we were able to produce highly promising outcomes, proving that deep learning models can identify misinformation on social media efficiently. The Bi-LSTM and LSTM models, specifically, performed well, with Bi-LSTM performing marginally better than LSTM, confirming the robustness of our approach in managing the subtleties of fake news detection. Moreover, our incorporation of advanced feature extraction methods, including sentiment analysis, allowed the models to capture the subtlety of language and context used in Twitter posts. By outperforming the capabilities of conventional models such as our deep learning models included logistic regression as well as random forest classifiers extremely efficient in categorizing fake news from true facts. This success indicates the capability of computer systems to aid the battle against false information in real-time on social media websites. In total, this study is able to effectively meet the objective of creating an automated system with high accuracy for detecting misinformation on Twitter, offering a scalable and effective solution for tracking and addressing the spread of wrong data. This work will pave the way for future advancements in the subject, contributing significantly to the larger body of research on disinformation detection and its applications to everyday issues.

Statements and Declarations

Ethical Approval

"The submitted work is original and not have been published elsewhere in any form or language (partially or in full), unless the new work concerns an expansion of previous work."

Consent to Participate

"Informed consent was obtained from all individual participants included in the study."

Consent to Publish

"The authors affirm that human research participants provided informed consent for publication of the research study to the journal."

Funding

"The authors declare that no funds, grants, or other support were received during the preparation of this manuscript."

Competing Interests

"The authors have no relevant financial or non-financial interests to disclose."

Availability of data and materials

"The authors confirm that the data supporting the findings of this study are available within the article."

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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