Factual News Verification

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ABSTRACT- In the digital age, disinformation has become a significant challenge, necessitating the development of effective detection systems. This study presents a Factual News Verification System that classifies news articles as either true or fake using machine learning algorithms. The system is implemented as a web-based platform, allowing users to register, log in, select a news category, and submit news articles for validation.

The system applies text preparation methods including cleaning and TF-IDF vectorisation to a dataset that includes both fake and authentic news in order to improve accuracy. A number of machine learning models, such as Multinomial Naïve Bayes, Logistic Regression, Decision Tree Classifier, and Passive-Aggressive Classifier, are trained and assessed. Key performance indicators like accuracy, precision, recall, and F1-score are used to evaluate these models; the ensemble model achieved an overall accuracy of 93.4%.

The proposed system provides a reliable and user-friendly platform for real-time news verification, helping to combat misinformation and promote informed decision-making.

Keywords ML, random forest, TF-IDF, classification, Multinomial Naïve Bayes, Decision Tree, flask, data pre processing.

I. INTRODUCTION

Social media and digital platforms' explosive expansion has greatly sped up the distribution of misleading information, presenting major problems for society. Misinformation, especially fake news, can affect democratic processes, disturb social cohesion, and sway public opinion. In order to solve this problem and improve digital literacy, advanced automated systems that can confirm the veracity of news are required.

In this work, we present a Factual News Verification System that detects false information using machine learning (ML) techniques. The system enables users to select a news category—such as politics, environment, entertainment, or movies—enter news articles, and receive real-time feedback on their authenticity. Our approach applies text preprocessing techniques, including data cleaning and TF-IDF vectorization, before classifying news articles using Classifier algorithms.

To evaluate the system's effectiveness, we assess model performance using key classification metrics, including Accuracy, Precision, Recall, and F1-score, achieving an overall accuracy of 93.4%. These metrics provide a comprehensive analysis by minimizing false positives and false negatives, ensuring a balanced approach to identifying both real and fake news. Additionally, we conduct extensive experiments to optimize feature selection, tune hyperparameters, and enhance model robustness. We also employ cross-validation techniques to ensure consistent model performance across various data subsets.

To further improve our system, we address challenges such as data imbalance, overfitting, and model generalization through the application of data augmentation techniques, regularization methods, and ensemble learning strategies. Our system is designed to operate in real-time, making it a valuable tool for journalists, policymakers, educators, and the general public seeking to verify news credibility quickly and accurately.

Beyond basic fake news detection, this work contributes to the development of scalable and automated solutions that can be integrated into web browsers, social media platforms, and news agencies to curb the spread of misinformation. Additionally, we look at the moral ramifications of AI-powered fact-checking, stressing the significance of using AI responsibly to avoid classification biases.

The findings of this study underscore the crucial role of technological interventions in fostering a media-literate and well-informed digital society, where individuals can critically evaluate information before sharing it. By leveraging machine learning for fact-checking, our system offers a reliable, efficient, and scalable solution to combat misinformation and promote truth in the digital era..

II. LITERATURE REVIEW

In order to improve classification accuracy, researchers have been examining a variety of machine learning and deep learning techniques in the field of fake news identification in recent years. Numerous research have shown how well various models work to identify false information, with each highlighting unique advantages and disadvantages.

Machine Learning-Based Approaches:

Sharma et al. employed Passive-Aggressive Classifier, Random Forest, and Logistic Regression, achieving notable accuracy in fake news classification. Similarly, Khanam et al. utilized XGBoost, while Pandey et al. applied Decision Tree and Logistic Regression, highlighting performance variations among models. Ahmed et al. (2017) emphasized the superiority of Linear SVM in detecting political misinformation, whereas Granik & Mesyura (2017) demonstrated that Naïve Bayes is effective for classifying fake news based on social media sources.

Deep Learning and Hybrid Models:

Recent advancements in deep learning have introduced more flexible models that adapt to evolving misinformation tactics.

Bugueño et al. explored Recurrent Neural Networks (RNNs) for propagation tree classification, while Alsaeedi and Al-Sarem enhanced CNN-based models through hyperparameter fine-tuning. Additionally, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have demonstrated strong capabilities in handling long textual dependencies, improving classification accuracy.

Hybrid models that combine multiple deep learning techniques have also been explored. Studies have shown that merging Convolutional Neural Networks (CNNs) and Bi-LSTM can enhance rumor detection performance. Shu et al. introduced dEFEND, a co-attention subnetwork that leverages both news content and user comments to refine fake news classification. Multi-task learning techniques like FDML have further improved detection by incorporating contextual news information.

Comparative Model Analysis:

M. F. Mridha et al. analyzed deep learning models like CNN and RNN, highlighting the effectiveness of GlobalMaxPooling1D and LSTM in improving classification accuracy. Jain et al. proposed a Naïve Bayes and SVM-based model, achieving 93.5% accuracy by integrating Natural Language Processing (NLP) techniques. M. E. H. Rafi et al. developed an automated fake news detection system that utilized .

Challenges and Future Directions:

Despite the effectiveness of existing models, challenges such as overfitting, data scarcity, and explainability of AI models remain concerns in fake news detection. Studies by Asghar et al. and Singhania et al. explored hybrid models that combine CNN, LSTM, and GRU, demonstrating their ability to preserve contextual information. Similarly, Z. Khanam et al. analyzed multiple supervised learning techniques, including XGBoost, Random Forest, Naïve Bayes, KNN, Decision Tree, and SVM. Their study concluded that XGBoost achieved the highest accuracy (~75%), followed by SVM and Random Forest (~73%). Furthermore, feature extraction and vectorization techniques such as Count Vectorizer and TF-IDF have been identified as key components in enhancing model performance.

Prior research has also investigated combining multiple ML models to improve classification accuracy. While Naïve Bayes-based models achieved around 74% accuracy, other hybrid approaches combining various ML techniques attained accuracy levels between 85% and 91%, though some studies relied on unreliable probability thresholds.

Author	**Algorithm**	**Application**	**Accuracy**	**Precision**
Sharma et al.	Passive-Aggressive Classifier, Random Forest, Logistic Regression	Fake news detection, misinformation control	85%	Moderate
Khanam et al.	XGBoost	Fake news classification, supervised learning	75%	High
Pandey et al.	Decision Tree, Logistic Regression	Fake news analysis, detecting misinformation	80%	Moderate
Granik & Mesyura	Naïve Bayes	Fake news classification from social media sources	74%	Low
Ahmed et al.	Linear SVM	Political misinformation detection	82%	High

Table 1: Summary Table for Literature Review

The efficacy and appropriateness of several (ML) models, such as XGBoost, Naïve Bayes, and SVM, for fake news detection are generally demonstrated by these works. With their own benefits and application contexts, methods like Passive-Aggressive Classifier and CNN-based hybrid models are frequently found to be effective in identifying misinformation. High classification accuracy and reliability are ensured by these models through the use of strong data preprocessing techniques like TF-IDF and NLP-based feature extraction. Web frameworks such as Flask simplify the deployment and integration of fake news detection systems, making it easier to implement real-time verification models. These developments highlight the crucial role of machine learning in combating misinformation and ensuring access to credible information in digital media.

III. Data Preprocessing

The dataset undergoes multiple preprocessing stages to ensure consistency, reliability, and improved classification accuracy. Initially, missing values and duplicate entries were identified and removed to maintain data integrity and prevent redundancy. The text was then standardized by converting all characters to lowercase, removing stopwords, special characters, punctuation, and numbers to focus on meaningful content. To further refine the text, contractions were expanded. Lemmatization was then used to reduce words to their base forms, preserving their semantic meaning while minimizing dimensionality. Additionally, URLs, email addresses, hashtags, and mentions were eliminated to avoid unnecessary noise. Informal language, slang words, and abbreviations were also expanded to their standard forms for better interpretability.

Once the text was cleaned. A vocabulary limit was imposed to improve computational efficiency and reduce overfitting. The dataset was then analyzed for class imbalance, and techniques like oversampling or undersampling were considered to balance the distribution of real and fake news. Finally, the dataset was split into training and testing subsets using stratified sampling to ensure equal representation of both classes, with an additional validation set used for hyperparameter tuning and model evaluation. These preprocessing steps ensured a refined dataset, optimized for effective feature extraction and improved classification performance

Heatmap: Patterns of association are revealed by the correlation heatmap, which visualizes links between variables. In order to facilitate feature selection and multicollinearity analysis, strong correlations are represented by lighter hues.

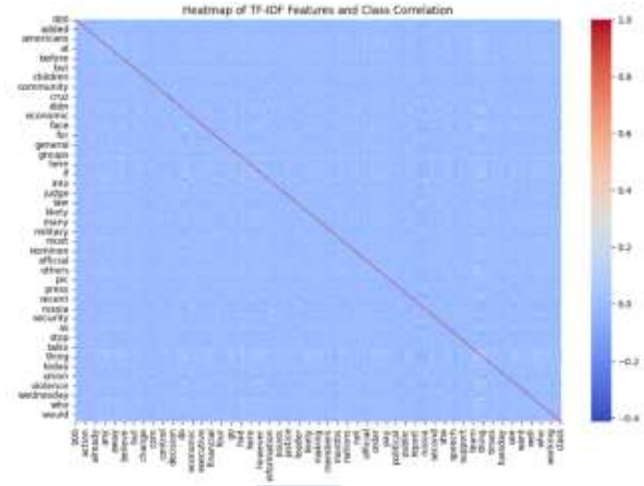

Fig 3.1: Heatmap

Classification Distribution : The classification distribution plot indicates an approximately balanced dataset in terms of treatment status, which facilitates unbiased model training and evaluation for predictive analysis.

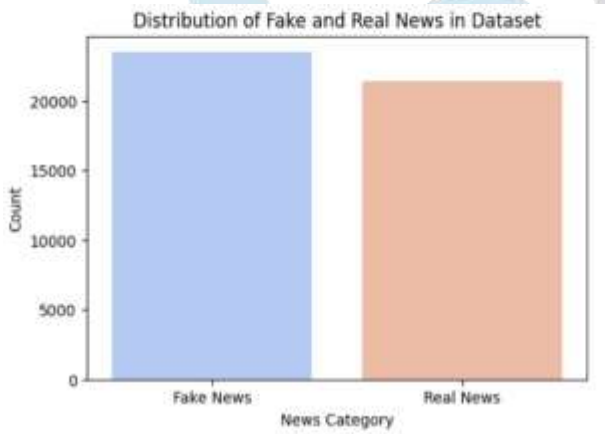

Fig 3.2: Classification Distribution

A. *Data Visualization*

The dataset was divided between training and testing subgroups to prevent overfitting and more precisely assess the model's performance. About 80% of the whole data, or 33316 records out of 44,916 records, are in the training set, while 20% of the total data, or 11605 records, are in the testing set. These preparation actions were essential in getting the data ready for training, which improved the model's generalization and prediction precision.

	Training	Testing	Validation
No of Rows	33316	8000	3605
No of Columns	5	5	5

Table 2: Train-Test-Split

IV. Methodology

The To ensure high-quality input for machine learning models, the process of verifying genuine news begins with the collection and preprocessing of datasets. The dataset comprises two separate files, **authentic.csv** and **fake.csv**, which contain news samples labeled as either authentic or fraudulent. These datasets are merged into a single dataset, forming the foundation for model training and testing. Given that the data originates from various sources, preprocessing is crucial for eliminating inconsistencies and ensuring uniformity.

The preprocessing phase includes handling missing values, removing duplicate entries, standardizing text formats, and eliminating special characters and stopwords. These steps enhance the dataset's usability and improve its effectiveness for machine learning models.

Furthermore, Term Frequency is used to transform textual data into numerical representations appropriate for model training. Vectorisation using Inverse Document Frequency (TF-IDF) is used. Furthermore, to improve model performance, feature selection approaches are used to find the most pertinent textual qualities that differentiate authentic news from fraudulent news.

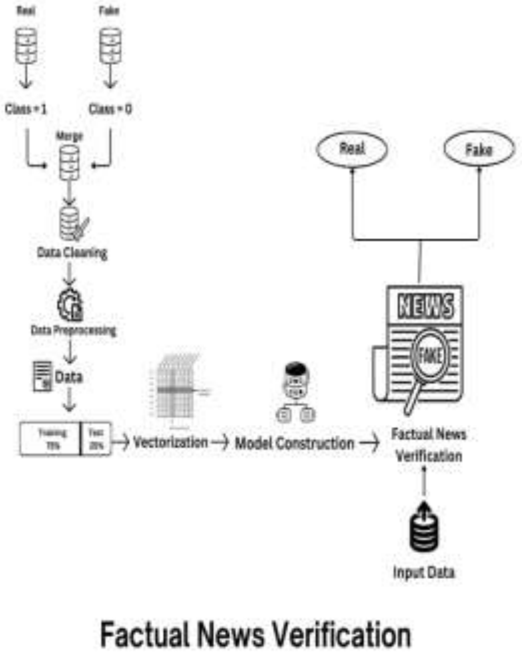

Fig 1: Model Architecture

A. Dataset Description

We utilized two datasets, Real.csv and Fake.csv, which contain labeled news samples for the factual news verification system. These datasets were merged into a single dataset to train a machine learning model capable of distinguishing between true (1) and fake (0) news based on user input.The dataset consists of textual content featuring various linguistic patterns that differentiate authentic information from misinformation. By structuring the dataset effectively, the system can identify patterns commonly found in fake news and use these insights to verify the authenticity of user-submitted content**.**

B. Dataset Preparation

The dataset undergoes multiple preprocessing stages to ensure classification consistency. Initially, inconsistencies are addressed by removing duplicate entries and missing values. To standardize the input, the text is converted to lowercase, and unnecessary elements such as stopwords, special characters, and punctuation are removed.To enhance feature representation, lemmatization is applied **.**

	title	text	subject	date	class
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017	0
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017	0
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017	0
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017	0
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017	0
5	Racist Alabama Cops Brutalize Black Boy While...	The number of cases of cops brutalizing and ki...	News	December 25, 2017	0
6	Fresh Off The Golf Course, Trump Lashes Out A...	Donald Trump spent a good portion of his day a...	News	December 23, 2017	0
7	Trump Said Some INSANELY Racist Stuff Inside ...	In the wake of yet another court decision that...	News	December 23, 2017	0
8	Former CIA Director Slams Trump Over UN Bully...	Many people have raised the alarm regarding th...	News	December 22, 2017	0
9	WATCH: Brand-New Pro-Trump Ad Features So Muc...	Just when you might have thought we d get a br...	News	December 21, 2017	0

C. Model Selection

To find the most pertinent textual characteristics for factual news verification, we used a combination of chi-square testing, correlation analysis, and TF-IDF weighting for feature selection. In order to lessen the impact of commonly used but meaningless phrases, TF-IDF (Term Frequency-Inverse Document Frequency) gave words significance scores according to their importance. Statistically significant terms that distinguish real news from fake news were found with the aid of chi-square analysis. To avoid overfitting and guarantee a more effective model, correlation analysis was utilised to eliminate superfluous features. In the end, these methods improved the model's accuracy and its capacity to generalise to new, unseen news inputs by enhancing the dataset's dimensionality reduction while maintaining crucial language patterns.

D. Model Development

To create an efficient system for verifying the accuracy of news, we investigated a number of machine learning methods, such as Multinomial Naïve Bayes, Logistic Regression, Decision Tree Classifier, and Passive-Aggressive Classifier. The preprocessed dataset, which included both actual and fraudulent news pieces, was used to train each model. The dataset was divided into training (80%) and testing (20%) sets in order to guarantee reliable model evaluation and avoid overfitting. We used Grid Search for hyperparameter tuning and Cross-Validation to optimise model performance in order to improve predicted accuracy. Furthermore, by integrating predictions from several classifiers, an ensemble approach was investigated to increase the system's dependability and efficacy in identifying false information.

E. Model Evaluation

We used common classification metrics, such as Accuracy, Precision, Recall, and F1-score, to assess how well the models distinguished between bogus and real news. In order to evaluate the models' capacity to distinguish between the two classes across a range of decision criteria, we also computed the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). To examine the variations in performance amongst models, we used statistical tests including McNemar's test and paired t-tests. Additionally, deeper understanding of misclassification patterns and the trade-off between accuracy and recall was made possible by confusion matrices and precision-recall curves, which improved model selection and optimisation techniques..

V. RESULTS & ANALYSIS

Predetermined performance measures are used to assess the efficacy of the factual news verification approach. Our method employs Accuracy, Precision, Recall, F-score, and Specificity as essential metrics to evaluate the model.

A confusion matrix is utilized to examine the model's performance by comparing the dataset's actual labels with the predicted labels (fake or real). This matrix provides a detailed breakdown of the model's predictions, allowing us to identify strengths and weaknesses in classification. Since factual news verification is a binary classification problem, the confusion matrix effectively highlights.

High Precision ensures that when the model classifies news as real, it is indeed factual, reducing the risk of misinformation.
High Recall indicates the model's ability to accurately detect fake news.
The F-score balances Precision and Recall, providing a more reliable performance measure.
Specificity ensures that fake news is correctly identified, reducing false alarms.
These evaluation metrics collectively contribute to optimizing the factual news verification system, ensuring improved accuracy and reliability in distinguishing between real and fake news.

Confusion Matrix: The confusion matrix depicts the classification performance, exhibiting a model that predicts only negative situations and no positive predictions, indicating an imbalanced outcome.

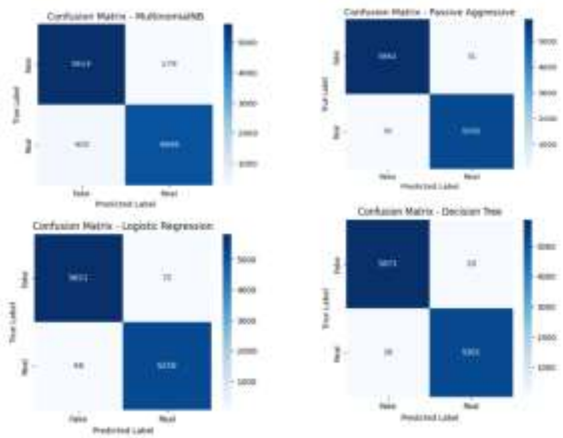

Fig 5.1: Confusion Matrix

ROC CURVE: The ROC curve illustrates the ability of our Fake News Detection model to distinguish between real and fake news. A high AUC (Area Under the Curve) value signifies strong classification performance, indicating that the model effectively differentiates between authentic and fraudulent news articles..

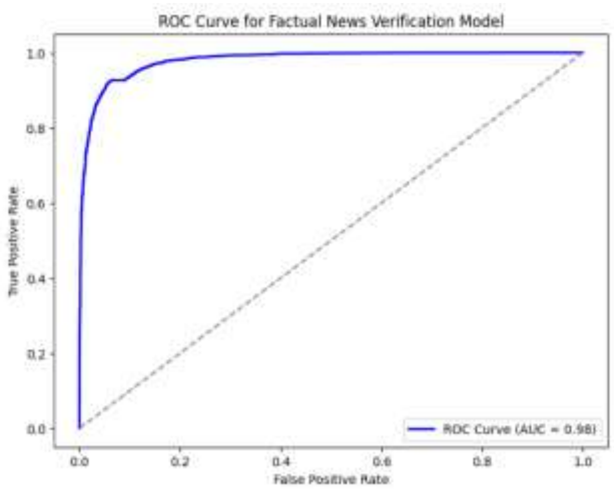

Fig 5.2: ROC Curve

Precision-Recall Curve: - Our Fake News Detection model's performance is assessed using the Precision-Recall curve, especially when there is a class imbalance. It highlights the trade-offs between correctly detecting false news and making sure that legitimate material is not misclassified, demonstrating how precision varies as recall rises. Better model efficacy in differentiating between fake and authentic news is indicated by a bigger area under the curve (AUC).

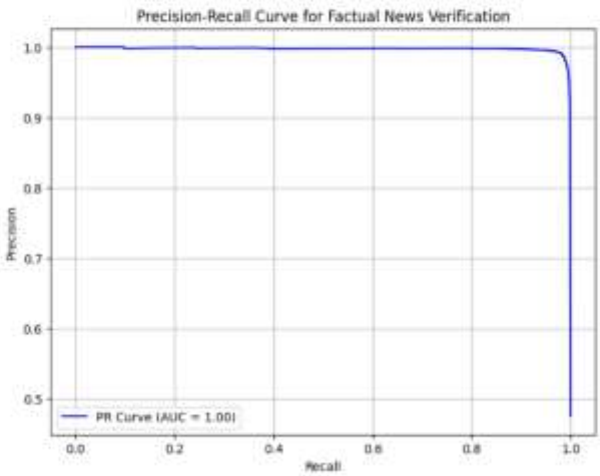

Fig 5.3: Precision-Recall Curve

VI. Conclusion

Considering This study demonstrates how well machine learning (ML) algorithms can reliably categorise news as real or fake by using linguistic and statistical indicators to confirm the authenticity of news material. The study shows how sophisticated computational methods can greatly improve the detection of false information, resulting in an information ecosystem that is more dependable and trustworthy. Early detection of fake news improves user knowledge and slows the spread of false information.

While the results are promising, challenges such as model bias, adversarial manipulation, and generalization to diverse news sources remain. Addressing these issues requires further research to refine algorithms, incorporate larger and more diverse datasets, and improve model interpretability to enhance user trust.

Moreover, future advancements in factual news verification could enable real-time analysis, where models continuously learn from new data, improving classification accuracy over time. Integrating ML models with browser extensions, social media platforms, and mobile applications could further empower users by providing instant credibility assessments for news content.

As ML technologies evolve, ensuring transparency, ethical considerations, and user-friendly implementations will be crucial in fostering public trust. Through collaborative efforts between data scientists, media organizations.

VII. Future Scope

The The developed machine learning model for factual news verification has significant potential for future advancements and applications. One promising direction is its integration into large-scale digital platforms, enabling real-time news authentication across various domains, including social media, news websites, and search engines. Deploying the model as an open-source tool could enhance its adaptability, allowing researchers and developers to refine its predictive capabilities across multiple platforms.

Future improvements could involve incorporating advanced deep learning techniques, such as transformer-based architectures, to enhance classification accuracy and scalability. Expanding the dataset by including diverse sources and multilingual news articles would improve the model's robustness and generalizability. Additionally, adaptive learning strategies, such as real-time model updates and user feedback mechanisms, could refine the model's accuracy and responsiveness to evolving misinformation tactics.

By integrating the system into web browsers, mobile applications, and media platforms, users could receive instant credibility assessments of news articles. These enhancements could strengthen misinformation detection efforts.

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