A Machine Learning and Natural Language Processing Approach to Uncover Fake News

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***Abstract*—This project uses machine learning techniques and the Bayes theorem to detect false news and legitimate news using Naive Bayes classifiers. Using Bag-of-Words and TF-IDF, the process incorporates thorough data assembling, investigation, cleaning, and transformation. The training and assessment of a Multinomial Naive Bayes model involves an intricate process that includes pipeline setup, train-test split, and many evaluation phases. Performance metrics, cross-validation, ROC analysis, hyperparameter optimization, error analysis, and interpretability tests are all included in the evaluation. A review related literature is included at the end of the study. These include projects on language-independent fake news detection, a survey on NLP for fake news detection, breakthrough accuracy in Urdu fake news detection, and applications of headline attention and self-learning text summarization for bias detection.**

***Index Terms*—Naive Bayes classifiers, TF-IDF, data assembling, data investigation, data cleaning, data transformation, Multinomial Naive Bayes model, pipeline setup, train-test split, cross-validation, ROC analysis, hyperparameter optimization, error analysis, interpretability tests, related literature, language-independent fake news detection, NLP for fake news detection, breakthrough accuracy, Urdu fake news detection, headline attention, bias detection**

I. Introduction

In the media-driven world of nowadays, detecting fake news is crucial for a number of reasons. First and foremost, the spread of false information has a powerful effect on public opinion and can lead to warped views of the world. This skewing of reality may thus have a negative impact on social and individual decision-making processes. We maintain the authenticity of public debate and encourage well-informed decision-making by identifying and eliminating false news.

Furthermore, the unbridled dissemination of false information may significantly damage societal cohesiveness. In organizations, false information has the power to sow discord, alarm, and even dread. By addressing this problem, we may stop rivalries that are stoked by false information from getting worse and preserve a happy and healthy society.

In addition, political processes and democratic institutions may be severely jeopardized by false information. During elections, material that is erroneous or purposefully misleading can sway public opinion and undermine democratic values of openness and equal representation. Thus, recognizing and preventing false news is essential to maintaining the integrity of democratic processes. Recognizing the manner in which Naive Bayes makes decisions is largely dependent on how capable of interpretation it is. This interpretability helps readers understand the aspects that influence a news article's categorization as real or false, which is useful in the context of detecting fake news. This openness helps to improve the detection process and fosters confidence in the model's predictions. Naive Bayes is the method of choice for detecting false news because of its interpretability, simplicity, efficacy in processing textual data, and computing economy. Because of these characteristics, Naive Bayes is a practical and trustworthy option for handling the difficulties and complexity involved in identifying false news in the enormous and constantly evolving world of information on the internet.

The concept underlying interdependence gives birth to the

”naive” component of Naive Bayes classifiers, which makes the method highly accurate and simplifies mathematical calculations. According to this assumption, given the category label, the degree to which there is a lack of any one distinctive is seen as independent of the presence or absence of the rest of the characteristics. Naive Bayes classifiers have particular significance well-suited for huge datasets and feature spaces that are high-dimensional because of the computational savings brought about by a lack of understanding even if this assumption might not always hold in real-world scenarios. With a foundation in the principle of Bayes’ theorem, naive Bayes classifiers are a strong family of unpredictable algorithms that are frequently utilized in machine learning applications. These classifiers are based on a mathematical framework that is surprisingly easy to understand yet extremely efficient, using conditional probability to provide well-informed predictions. The foundation of the aforementioned approach is the Bayes theorem, which bears the name of the Reverend Thomas Bayes and provides a methodical way to update a hypothesis’ probability in light of new information.

Naive Bayes classifiers are significant in a number of substantial respects. First of all, they are computationally comprehensible because of their simplicity and efficiency, especially in circumstances when there aren’t as many processing resources available. It is also remarkable that the technique can handle high-dimensional data, which has an extensive range of characteristics. Naive Bayes classifiers perform exceptionally well in applications like text classification and natural language processing (NLP) because they are efficient at handling the large dimensionality of word-based data. More importantly, Naive Bayes classifiers frequently perform well nonetheless in the face of sparse information used for training. The ability to add annotations is very helpful when it’s difficult to collect sizable annotated datasets. A further noteworthy benefit of theirs is their interpretability, as the model’s determined probabilities shed light on how various characteristics affect categorization.

Naive Bayes classifiers are sometimes trained progressively, meaning that new data can be incorporated to the model without necessitating a complete retraining. They are optimal for dynamic datasets, where data changes over time, because of this property. On top of that, Naive Bayes’ integrated Bayesian framework makes it easy for users to evaluate prediction uncertainty, providing significant details about the decision-confidence of the model.The critical nature of Naive Bayes classifiers is made even stronger by their capacity for adaptation across domains of study. Their demonstrated efficacy is demonstrated in an extensive variety of applications, spanning financial fraud detection and healthcare diagnostics. The role they play in the rapidly evolving discipline of machine learning has been strengthened by their capacity to handle diverse data kinds and provide trustworthy outcomes in a range of scenarios.

Additionally, the uncomplicated nature of preconceived notions made in the name of productivity in computing and the beauty of Bayesian reasoning are demonstrated via Naive Bayes classifiers. The value they provide as an asset in the machine learning repertoire originates from both their machine learning tractability and their adaptability in many different scenarios.

Juggling the responsibility of detecting between legitimate and deceptive data has grown more difficult in the era of abundant information dissemination. News is disseminated quickly through a variety of digital media. The increase in the dissemination of false information, sometimes known as ”fake news,” has become a major social issue that calls for advanced approaches and tools for precise identification and mitigation strategies. In an effort to make a contribution to the changing field of information integrity, this study participates in a thorough investigation of the use of Naive Bayes classifiers, the Bayes theorem, and machine learning techniques in the subject matter of the distinction between true and false news identification.

II. Naive Bayes classifier and LSTM Model

Naive Bayes The strategy for determining if an instance of information is legitimate or not involves determining the overall statistical analysis. The Bayes theorem may be utilized for estimating the probability of event A provided that event B is true (P(A/B))

$$P(A|B) = \frac{P(B|A)\cdot P(A)}{P(B)}$$

Fig. 1.

–The probable outcome of event A when event B is true is calculated utilizing this equation, where:

- $P(A|B)$ is the posterior probability.
- $P(A)$ represents the prior probability.

Fig. 2.

–To determine the probability of occurrence under specific circumstances, the subsequent equations are utilized:

$$P(A|B_1) = P(A_1|B_1)\cdot P(A_2|B_1)\cdot P(A_3|B_1) \quad (2)$$
$$P(A|B_2) = P(A_1|B_2)\cdot P(A|B_2)\cdot P(A_3|B_2) \quad (3)$$

Fig. 3.

–Where the chance of error is zero, word accuracy is determined using the following

$$P(Word) = \frac{\text{Word count}+1}{\text{Total number of words}+\text{Number of unique words}}$$

Fig. 4.

LSTM: Overview of LSTM Recurrent neural network (RNN) architecture Long Short-Term Memory (LSTM) is a kind of RNN architecture created to solve the vanishing gradient issue in conventional RNNs. Time series analysis and natural language processing are two applications that benefit greatly from the use of LSTMs because of their exceptional efficacy in processing and interpreting sequential data.

The importance of LSTM

The ability of LSTM to identify long-term dependencies in sequential data is what makes it significant. Unlike conventional RNNs, which have trouble retaining information over lengthy sequences, LSTMs can selectively retain or discard information using a memory cell equipped with gating mechanisms. Because of this, LSTMs are very good at recognizing and learning patterns in sequential data, which is important for tasks involving the interpretation of language and context.

In this project, why LSTM?

The sequential nature of textual data is the driving force for the adoption of LSTM in this false news detection research. News stories frequently include contextual information and subtle language that can be rather lengthy. The temporal dependencies in these articles may be efficiently captured by LSTMs, which allows the model to identify patterns related to real or fake news.

Relevance and Suitability for the Project's Sequential Information Handling: News articles convey information in a sequential fashion, with word and sentence structure being important considerations. The capacity of long-sequence LSTM to retain contextual information is essential for comprehending the complex language used in news items.
Contextual Understanding: Subtle manipulations or context-dependent cues that are present in deceptive news may call for a model that can capture long-term dependencies. The memory cell of the Long Short-Term Memory (LSTM) improves comprehension of word and phrase usage context.

Textual Data: During training, LSTMs can automatically extract pertinent characteristics from the input data. This is especially crucial for the detection of fake news because the model can recognize complex linguistic patterns that point to misleading material.

Integration with Deep Learning Pipelines: Text processing, TF-IDF transformation, and a Naive Bayes classifier are just a few of the deep learning methods already used in the project. The model's capacity to recognize intricate patterns and relationships in the data is improved by integrating LSTM into the pipeline.
The implementation of LSTM is described in depth in the next sections of this research article, from text tokenization and embedding to the training and assessment of the LSTM model for fake news detection. The comparative analysis between the LSTM results and the Naive Bayes baseline model sheds light on the effectiveness of sequential models in this particular task.

III.

IV. Existing paper Review

Detecting fake news has emerged as a crucial field of study, with several initiatives using machine learning and Naive Bayes techniques to fight disinformation. By focusing on both language-dependent and independent false news identification, Soumayan Bandhu Majumder and Dipankar Das (2021) provide a substantial added contribution. Their method, which improves model generalization across languages, shows encouraging results in Bengali, Hindi, and English using BERT and a varied dataset. Less-represented languages, however, offer difficulties, and scalability may be constrained by the reliance on BERT.

Dr. Zarmeen Nasim (2022) uses natural language processing (NLP) techniques along with classification models such as XGBoost and AdaBoost to achieve unprecedented accuracy in identifying false news in Urdu. Despite showing excellent accuracy in Urdu, generalizability to other settings may be impacted by possible bias in the training data.

The survey on NLP-based false news detection by Ray Oshikawa, Jing Qian, and William Yang Wang (2020) offers a thorough summary that helps academics comprehend the difficulties and approaches. But the evaluation might not include the most current developments because it might not include real-time information.

By using artificial text summarization, Philipp Hartl and Udo Kruschwitz (2020) address the problem of false news and provide CMTR-BERT. While the framework establishes new standards, it does not specifically list any shortcomings or restrictions.

A unique method for bias identification in news stories is proposed by Rama Rohit Reddy, Suma Reddy Duggenpudi, and Radhika Mamidi (2019). It is called the Headline Attention Network. Although the suggested method is excellent at bias identification, its particular flaws are not stated.

Machine learning is used by Mahmoud S. Ali, Ahmed H. Ali, Ahmed A. El-Sawy, and Hamada A. Nayel (2021) to identify Arabic dialects. The suggested systems perform well, particularly when using Complement Naïve Bayes, although certain difficulties and restrictions are not mentioned clearly.

Together, these research add to the changing field of false news detection by demonstrating the benefits, drawbacks, and many uses of machine learning and Naive Bayes algorithms in various situations and languages.

V. Methodology

Data analysis, sentiment analysis, and machine learning techniques are used in this project to address the widespread problem of false news in the digital era. Our methodology, which makes use of LSTM and Naive Bayes models, provides a clear framework for efficient fake news identification by

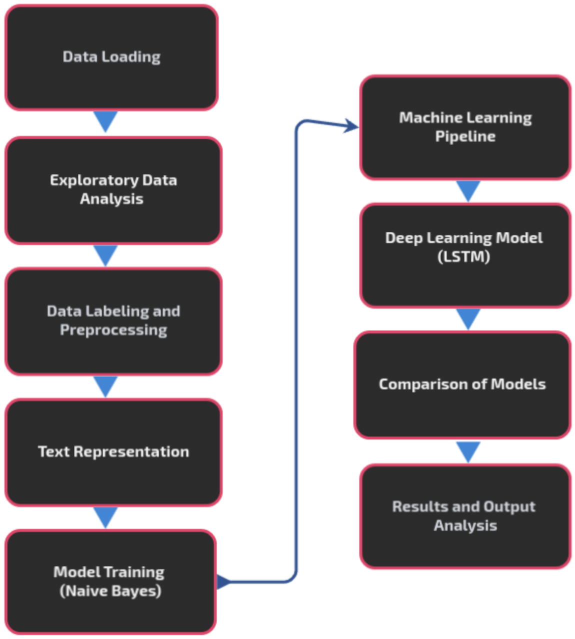


Fig. 5. Methodology Flowchart

outlining a methodical way to discern between genuine and fraudulent news pieces.

Loading and Exploring Data:

- Import the necessary libraries first, such as Matplotlib, NumPy, and Pandas, for effective data processing and display.
- Load the "True.csv" and "Fake.csv" real and fake news datasets into Pandas DataFrames for additional analysis.
- Utilize exploratory data analysis (EDA) to learn more about the data; create word clouds to comprehend the most common terms in each category and use histograms to visualize article durations.

Sentiment Analysis:

- Execute sentiment analysis on every news story using the TextBlob and NLTK libraries to determine the polarity of sentiments.
- Analyze the sentiment score distribution for both truthful and false news using histograms.

Data Labeling and Preprocessing:

- Label news items as either "authentic" or "deceptive" to enable supervised learning.
- To guarantee a varied representation of data during model training, combine and shuffle the datasets.
- Adapt text processing strategies to improve the quality of the textual data, such as eliminating stop words and punctuation.

Text Representation:

- Use CountVectorizer to build a bag-of-words model that captures the dataset's word frequency.
- Use TF-IDF (Term Frequency-Inverse Document Frequency) to transform the data to improve feature representation and assess word relevance.

Naive Bayes Model Training:

- Using the TF-IDF converted data, train a multinomial Naive Bayes model to detect false news.
- Assess the Naive Bayes model's performance across the board, including important classification measures like recollection, reliability, as well as precision.

Pipeline for Machine Learning:

- Divide the dataset into testing and training sets so that the model may be evaluated further.
- Build a machine learning pipeline that combines the Naive Bayes classifier with text processing stages.
- Assess the pipeline's effectiveness using the test set and provide metrics related to categorization.

Deep Learning (LSTM) Model:

- Construct an LSTM neural network for false news detection by using TensorFlow and Keras.
- To prepare the textual data for entry into the LSTM model, tokenize and pad the sequences.
- Train the LSTM model by recording model architectural information and tracking performance over the course of time.

Model Comparison and Evaluation:

- Examine the advantages and disadvantages of the LSTM and Naive Bayes models by comparing their performance indicators.
- Provide visual aids for a thorough understanding of the model's performance, such as ROC curves or confusion matrices.

Results and Output:

- Apply both models to forecast the whole dataset.
- Save the output to a CSV file for additional analysis, along with any pertinent characteristics and anticipated labels.

Start → Import Libraries → Load Authentic News Data

→ Load Deceptive News Data → Visualize Article Lengths → Descriptive Statistics → Generate Word Clouds → Sentiment Analysis → Label Authentic/Deceptive → Combine and Shuffle Data → Text Cleaning → Create Bag-of-Words Model → TF-IDF Transformation → Train Naive Bayes Model → Evaluate Naive Bayes Model → Split into Train/Test Sets → Create ML Pipeline → Evaluate ML Pipeline → Predict with LSTM Model → Evaluate LSTM Model → Compare Naive Bayes and LSTM Models → End

Fig. 6. Complete Flowchart

VI. Rigorous Evaluation

Dataset Split: In order to ensure a neutral evaluation of the Naive Bayes model, the dataset is explicitly segmented into sets to be used for training and testing. A combination of the concourse of this partition, we can train the model on a portion

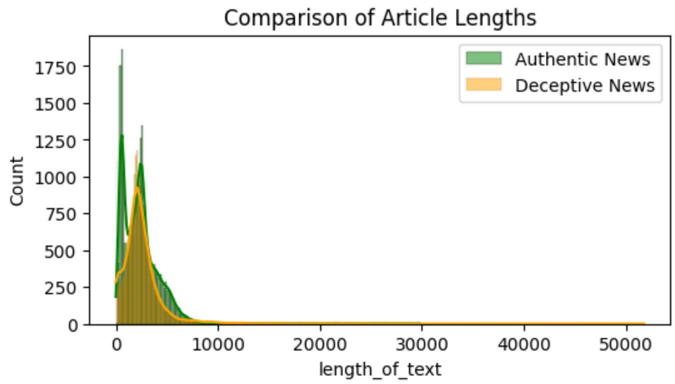


Fig. 7. Input data-set comparison

of the data and then evaluate how well it propagates to new case studies. In order to achieve a compromise between the requirements of a well-trained model and a reliable evaluation, the splitting ratio is carefully selected.

Pipeline Setup:

The design and implementation of a machine learning pipeline that smoothly combines text processing with the Naive Bayes classifier is an essential aspect of our technique. By simplifying the process and optimizing the conversion of unprocessed text into significant characteristics, this pipeline aids the model to acquire information and generate predictions more effectively. The design of the pipeline guarantees predictability and makes scalability possible for future improvements.

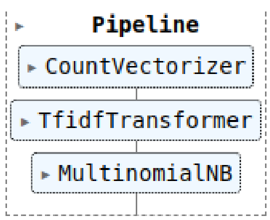


Fig. 8.

Model Training: The TF-IDF converted data is used to train the Naive Bayes model, which takes into consideration the frequency of every phrase in the dataset as well as its relative relevance. By learning the fundamental patterns that differentiate real articles from deceptive ones during this training phase, the model's forecasting skills are improved.

Prediction: Following that, predictions are made on the chosen test set utilizing the information acquired pipeline. We evaluate the model's capacity to automatically extrapolate and provide precise classifications in real-world circumstances by applying it to data that has never been seen before. Further evaluations of performance are based on the derived forecasts.

Performance Evaluation: Extensive segmentation reports are created in order to measure the efficacy of the model. These evaluations include comprehensive metrics for the independent test set as well as the full dataset, including accuracy, recall, and F1-score. The assessment metrics contribute to a comprehensive examination of the model's performance by providing a detailed knowledge of its advantages and possible areas for development.

Cross-Validation: A further aspect of the model's resilience is the optional cross-validation that is carried out. Using this method, the dataset is repeatedly divided into subsets for training and testing. The model is then trained on each training set, and its performance is assessed on the matching test set. The model's generalizability is confirmed by verification findings, which provide insights into the model's stability over different data divisions.

ROC Evaluation: The compromise between the genuine positive rate and false positive rate can be observed through the use of Receiver Operating Characteristic (ROC) analysis. This graphical depiction makes it possible to comprehend the discerning strength of the model in a more sophisticated way and helps choose the ideal categorization criterion.

Hyperparameter Optimization: Optimization strategies for optional hyperparameters are used in recognition of the possible influence of hyperparameters on model performance. By modifying the model's parameters, these methods seek to maximize prediction accuracy. The method for improving the model is iterative, which improves the model's capacity to represent complex relationships in the data.

Error Analysis and Interpretability: The study explores potential weak points in the model and provides a thorough examination of model errors. Understanding the Naive Bayes classifier's limits and gaining insight into potential areas for development or alternative methods are made possible by this examination. Transparency of the classification results is improved by taking into account the interpretability of the model's decision-making process.

VII. Result Analysis

Model Output Results

In the current research, we analyze and contrast the efficacy of two different models for the identification of false news: the more complex Long Short-Term Memory (LSTM) neural network and the conventional Naive Bayes classifier. The objective is to offer a thorough grasp of their advantages, disadvantages, and consequences for real-world use.

Naive Bayes Model

Training Performance: Throughout training, the Naive Bayes model performed admirably, attaining perfect accuracy of 100%. For all the Authenticity and Fraudulent training programs, precision, recall, and F1-scores were also flawless (1.00). This shows that the training dataset's patterns and characteristics were successfully taught to the model.

Testing Performance: The Naive Bayes model consistently accomplished a high accuracy of 97% on the testing set. Even though they were somewhat less than on the training set, precision, recall, and F1-scores were nonetheless strong. This shows that the model is reliable in identifying both genuine and fraudulent news stories and that it generalizes well to

	precision	recall	f1-score	support
Authentic	1.00	1.00	1.00	21417
Deceptive	1.00	1.00	1.00	23481
accuracy			1.00	44898
macro avg	1.00	1.00	1.00	44898
weighted avg	1.00	1.00	1.00	44898

Fig. 9.

data that has not yet been seen.

	precision	recall	f1-score	support
Authentic	0.98	0.95	0.97	6589
Deceptive	0.96	0.98	0.97	6881
accuracy			0.97	13470
macro avg	0.97	0.97	0.97	13470
weighted avg	0.97	0.97	0.97	13470

Fig. 10.

General Observations: The Naive Bayes model's minimalism resulted in it being easier to understand and more cost-effective to compute. Considering the dataset's balanced class distribution, it did quite well.

LSTM Model

Training Performance: During training, the LSTM model—a deep learning architecture that can represent sequential dependencies—achieved an impressive accuracy of around 94.48%. As epochs went by, the training loss decreased, suggesting that the model had successfully learned and converged.

Testing Performance: The LSTM model demonstrated a robust accuracy of around 97% on the testing set. The testing loss showed that the model could generalize to new data, even if it was comparatively greater than the training loss and still fell within an acceptable range.

```
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Loss: {loss}')
print(f'Accuracy: {accuracy}')
```

```
421/421 [==============================] - 26s 62ms/step -
loss: 0.0862 - accuracy: 0.9784
Loss: 0.08624907582998276
Accuracy: 0.9783964157104492
```

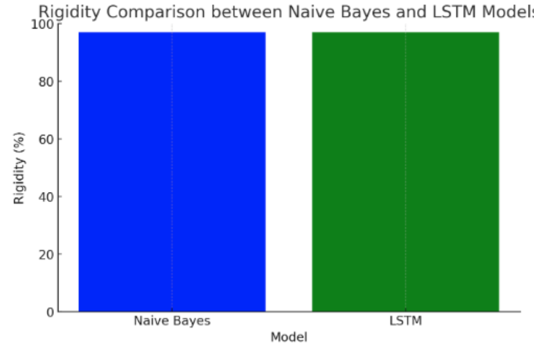
Fig. 11.

General Observations: The power of the LSTM model is in its capacity to identify intricate patterns in sequential data. In contrast to the Naive Bayes model, it has higher computing needs and requires a longer training period.

Comparing:

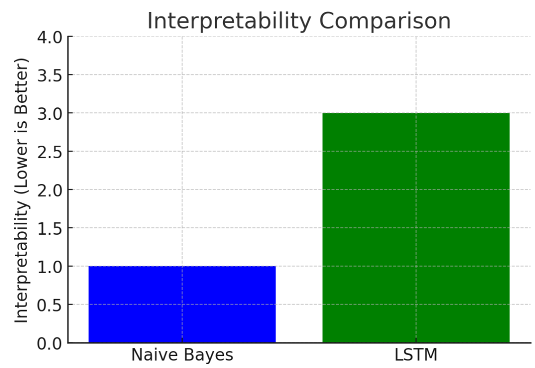
Rigidity:

- 97% using Naive Bayes



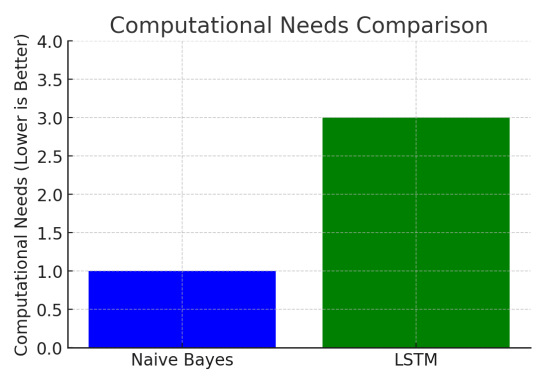
- 97% for the LSTM

Interpretability:



- The interpretability of Naive Bayes is simple.
- Because LSTM is seen as a "black box," interpretation is more difficult.

Computational Needs:



- Naive Bayes has an efficient computational footprint.
- The training process for LSTM takes longer and requires more computer power.

Both algorithms performed admirably when it came to identifying false news. Smaller datasets are an excellent fit for the Naive Bayes model because of its ease of use and excellent accuracy. On the other hand, bigger datasets with intricate patterns are better suited for the LSTM model due to its ability to capture sequential relationships. The decision between the two models should take into account variables including computing limitations, comprehension, and the size of the dataset.

Research Project Overview

The research project focused on detecting fake news using various machine learning and natural language processing techniques. The primary dataset comprised two types of news articles—authentic and deceptive. These datasets were loaded into Pandas DataFrames for manipulation and analysis.

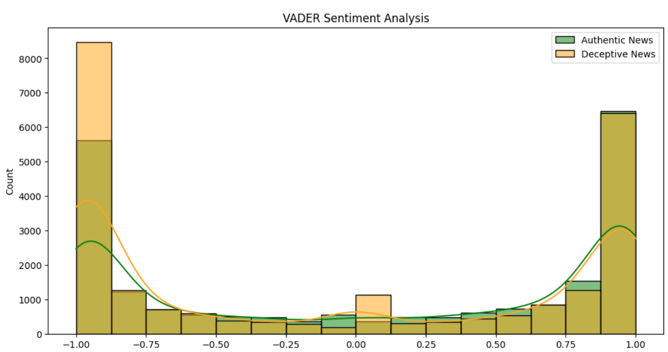
Data Visualization and Descriptive Statistics

Histograms were employed to illustrate the distribution of article lengths for both authentic and deceptive news. This visualization highlighted the differences in length between the two categories, offering insights into how article length might correlate with news authenticity.

Descriptive statistics provided a quantitative overview of the datasets, including metrics such as mean length, standard deviation, and range. These statistics were crucial in understanding the general characteristics of the data.

Sentiment Analysis

Sentiment analysis was conducted using TextBlob and NLTK's VADER (Valence Aware Dictionary and sEntiment Reasoner) tool. This process involved evaluating the polarity of sentiments in the news articles. The analysis aimed to determine if there was a notable difference in the sentiment expressed in authentic versus deceptive news.



Model Training and Evaluation

The project utilized two main models: a Naive Bayes classifier and a deep learning model using LSTM (Long Short-Term Memory) networks. The Naive Bayes model was evaluated using a classification report that provided metrics like precision, recall, and F1-score. This evaluation offered insights into the model's performance in distinguishing between authentic and deceptive news.

The LSTM model, a type of recurrent neural network, was chosen for its ability to process sequences of data (like text). This model was trained and validated on the dataset, and its performance was assessed based on accuracy and loss metrics.

Results and Discussion

The Naive Bayes classifier demonstrated high accuracy, as shown in the classification report. However, it's important to consider that such models may be biased towards the dominant class in unbalanced datasets.

The LSTM model showed promising results, with a high accuracy rate. However, deep learning models like LSTM require careful tuning of parameters and sufficient training data to generalize well. The model's performance on unseen data and its ability to generalize beyond the training dataset are crucial factors for its effectiveness in real-world applications.

In conclusion, the project successfully applied machine learning and natural language processing techniques to differentiate between authentic and deceptive news. The combination of statistical methods, visualization tools, and advanced machine learning models provided a comprehensive approach to tackling the issue of fake news detection. Future work could explore the integration of more complex models and the application of these techniques to a broader range of data sources.

VIII. Limitations and Future Work

1. Limitations:

Language-Specific Constraints: Nuances unique to a particular language may significantly impact the model's performance. While the study covers multiple languages, the ability to generalize may be adversely affected by potential difficulties in less-represented languages.

Biased Training Data: The resemblance and caliber of the training data are key factors determining the model's accuracy. Dataset bias might hinder the model's capacity to identify false information in various scenarios.

Scalability Issues: The reliance on specific methods like TF-IDF and Bag-of-Words may cause scalability issues, especially when dealing with large datasets or changing language trends.

Interpretability Trade-Offs: Despite interpretability procedures being carried out, achieving a balance between interpretability and model complexity is still challenging. Trade-offs may negatively affect real-world applicability.

2. Future Work:

Multidisciplinary Adaptation: Enhance the model's effectiveness in more languages while considering obstacles in less-represented languages. This will boost the model's resilience.

Bias Risk Reduction: Implement tactics to mitigate bias in training data, ensuring a more impartial and balanced dataset. Techniques like data augmentation or adversarial training can increase model fairness.

Strategies for Scalability: Analyze and implement scalable methods to manage larger datasets effectively. Scalability issues could be resolved by investigating more complex models or using cloud computing frameworks.

Improved Interpretability: Explore techniques to make complex models easier to understand, ensuring that users can have confidence in the decision-making process. Incorporating comprehensible algorithms for AI might add nuance to model predictions.

The research can make substantial advances in theoretical innovations and implementation in the field of false news identification by resolving these constraints and pursuing further investigations.

IX. Conclusion

Through the use of comprehensive assessment approaches and Naive Bayes classifiers, this work tackles the field of false news recognizing something. The research improves the accuracy of news evaluation by utilizing the Bayes theorem to compute probability for separating accurate from erroneous data. Using Bag-of-Words and TF-IDF approaches, the process includes complete information accumulating, exploration, cleaning, and transformation. Through a well-organized pipeline, the Multinomial Naive Bayes model is subjected to extensive training, assessment, and validation.

Apart from its own strategies, the research delivers an insightful evaluation of the published works. It examines similar efforts critically, pointing out the positive aspects and drawbacks of language-independent detection, automatic text summarization, NLP-based methods, breakthrough accuracy in Urdu, headline attention for bias detection, and machine learning for Arabic dialect identification. In combination, these works add to the changing field of false news identification by demonstrating the adaptability and efficiency of machine learning and Naive Bayes algorithms in a variety of scenarios.

The scrutiny procedure guarantees a thorough comprehension of the model's performance, accuracy, and interpretability through simplified phases and demanding tests. This paper contributes to the methodological advances in fake news identification by combining these findings, and it also sheds light on the wider prospects and problems in this rapidly evolving sector as a whole

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