International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Detection of Fake News Using Different Machine Learning Models

Nikil Kumaran K[1], Dr. Chitra K[2]

[1]UG Student, Department of Computer Science, Sri Krishna Adithya College of Arts and Science, Coimbatore.

[2]Assistant Professor, Department of Computer Science & Dean of Research, Sri Krishna Adithya College of Arts and Science, Coimbatore.

ABSTRACT :

The rapid proliferation of fake news on digital platforms poses a critical challenge, influencing public opinion and threatening the integrity of information dissemination. Traditional approaches to detecting fake news often rely on computationally intensive models, limiting their applicability in resource-constrained environments. This study presents a streamlined, efficient fake news detection system utilizing machine learning techniques. Focused on lightweight methodologies, the system leverages Logistic Regression and other models combined with Term Frequency-Inverse Document Frequency (TF-IDF) feature extraction. Google Colab is employed as the computational platform, offering scalability, accessibility, and cost-effectiveness. This streamlined pipeline provides an accessible and scalable tool for combating misinformation, emphasizing simplicity, computational efficiency, and real-world applicability.

Introduction :

The proliferation of digital platforms has revolutionized information dissemination, fostering global connectivity and empowering individuals to share knowledge seamlessly. However, this accessibility has also enabled the rapid spread of fake news—misinformation designed to deceive and manipulate public perception. Fake news presents significant risks, influencing critical areas such as elections, public health, and societal trust.

Addressing the challenges of fake news detection requires solutions that balance accuracy, efficiency, and scalability. Traditional methods like manual fact-checking are labor-intensive and struggle to match the pace of misinformation spread, while many advanced machine learning (ML) approaches, despite their accuracy, demand extensive computational resources that limit their practical application in resource-constrained settings.

This study introduces a streamlined ML-based approach to fake news detection, focusing on simplicity without sacrificing effectiveness. The proposed workflow encompasses data collection, preprocessing, train-test data splitting, feature extraction using the TF-IDF technique, model training, and predictive system development. Lightweight algorithms such as Logistic Regression and Passive Aggressive Classifiers are employed, demonstrating that robust results can be achieved with minimal computational overhead. Additionally, leveraging Google Colab as a cloud-based platform ensures scalability and accessibility for users with limited hardware capabilities, making this solution both practical and impactful.

Related work :

The detection of fake news has garnered significant attention due to its pervasive impact on society. Researchers have proposed various methodologies, leveraging advances in machine learning and natural language processing (NLP).

[1] Uma Sharma et al. explored machine learning models such as Naïve Bayes, Random Forest, and Logistic Regression, coupled with TF-IDF feature extraction, achieving notable accuracy on manually labeled datasets. Their study highlighted the importance of robust preprocessing techniques, including the removal of punctuation, stemming, and stopword filtering, in enhancing classification performance.

[2]Jeffrey Huang investigated binary classification approaches to identify fake news, utilizing datasets from Kaggle. His study emphasized the application of simpler yet effective methods such as Passive Aggressive Classifiers and Long Short-Term Memory networks. A key takeaway from Huang's work was the efficacy of analyzing language patterns instead of relying on factual content for verification, which is often time-consuming and resource-intensive. The use of TF-IDF and bag-of-words representations, combined with classifiers, yielded impressive accuracies, particularly with the Passive Aggressive Classifier achieving near-perfect results.

[3] Sairamvinay Vijayaraghavan et al. analyzed various pre-training and fine-tuning models, including Word2Vec, CountVectorizer, and TF-IDF for text representation, followed by classification with Logistic Regression, Support Vector Machines, and neural networks. Their findings demonstrated that context-preserving methods like TF-IDF and neural models such as LSTMs significantly improve fake news detection accuracy. The importance of preprocessing, including stopword removal, punctuation stripping, and sentiment analysis, was reiterated as essential for reducing noise in datasets and improving the learning process. Their experiments also underscored the potential of ensemble models, combining vectorization techniques with advanced classifiers to achieve superior performance.

Proposed Methodology :

The proposed system for fake news detection follows a structured workflow designed for simplicity, efficiency, and accessibility. The dataset, sourced from publicly available platforms like Kaggle, provides labeled examples of fake and real news articles. Google Colab, a free and cloud-based computational platform, is utilized to ensure the system is accessible to users with limited hardware resources. Data preprocessing involves several steps, including the removal of stopwords and punctuation, normalization of text data to lowercase, handling of missing values, and stemming to reduce words to their root forms. These steps prepare the raw data for machine learning by ensuring consistency and enhancing feature quality.

Feature extraction is performed using the TF-IDF (Term Frequency-Inverse Document Frequency) technique, which transforms text into a numeric format while capturing the importance of words within the dataset. The preprocessed data is then split into training and testing subsets, typically in an 80:20 ratio, to facilitate model evaluation. Two lightweight machine learning models—Logistic Regression and Passive Aggressive Classifier—are employed for training. These models are chosen for their efficiency and effectiveness in binary classification tasks.

The system's performance is assessed using metrics such as accuracy, precision, recall, and F1-score, ensuring reliable evaluation of its ability to distinguish fake news from real news. Once trained, the model is integrated into a predictive system that processes new data through the same pipeline, predicting whether the input is fake or real news. Additionally, the system supports iterative refinement by allowing new data to be fed into the model, enabling continuous improvement over time. This comprehensive and accessible approach demonstrates the potential for lightweight machine learning techniques to address the challenges of fake news detection effectively.

Workflow :

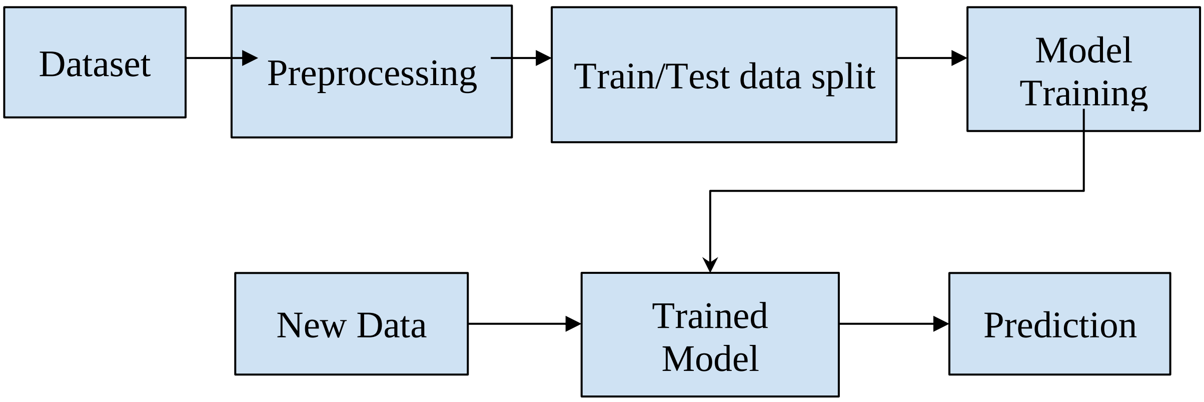
This project follows a structured workflow to build an efficient and accessible fake news detection system, utilizing lightweight machine learning techniques and accessible cloud-based resources.

1. **Data Collection**

   The dataset for this project is sourced from publicly available platforms like Kaggle. These datasets provide labeled fake and real news articles, ensuring sufficient data for training and testing machine learning models.
2. **Cloud-Based Computational Setup**
   The project leverages Google Colab, a free and cloud-based platform, for implementation. Google Colab provides the necessary computational power for data processing and model training, ensuring accessibility even for users with limited hardware resources.
3. **Data Preprocessing**
   Preprocessing is a crucial step to prepare raw data for machine learning. The preprocessing steps include:
   - **Removal of Stopwords and Punctuation:** Enhances the focus on meaningful words.
   - **Normalization:** Standardizes text data to lower case.
   - **Handling Missing Values:** Identifies and replaces missing or null values in the dataset to maintain consistency.
   - **Stemming:** Reduces words to their root forms, ensuring uniformity in features.
4. **Feature Extraction**
   Text data is transformed into a numeric format using the **TF-IDF (Term Frequency-Inverse Document Frequency)** technique. This method efficiently captures the importance of words in each document relative to the entire dataset, enabling the models to focus on significant features.
5. **Train-Test Data Split**
   The dataset is divided into training and testing subsets, typically with a ratio like 80:20, to evaluate the model's performance. This step ensures that the model generalizes well on unseen data.
6. **Model Training**
   Two machine learning models are employed:
   - **Logistic Regression:** A lightweight and interpretable algorithm suitable for binary classification tasks like fake news detection.
   - **Passive Aggressive Classifier:** A fast and resource-efficient algorithm, ideal for handling large-scale data in an online learning context.
7. **Model Evaluation and Accuracy Testing**
   After training, the models are evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into the system's effectiveness in distinguishing fake news from real news.
8. **Predictive System**

   The trained model is used to build a predictive system. This system accepts new[1] data, processes it through the preprocessing and feature extraction pipeline, and predicts whether the input is fake or real news.

[1]



Benefits of the Proposed System :

1. **Efficiency and Simplicity**
   - Utilizes lightweight models like Logistic Regression and Passive Aggressive Classifier, which offer high efficiency without the need for extensive computational resources.
   - The use of a single feature extraction technique (TF-IDF) simplifies the workflow while maintaining robust performance.
2. **Accessibility**
   - By leveraging Google Colab, the system ensures accessibility to cloud-based computational resources, making it feasible for users without advanced hardware setups.
   - Free and publicly available datasets from platforms like Kaggle lower entry barriers for implementation and testing.
3. **Scalability**
   - The system can handle large datasets due to the efficient algorithms and preprocessing techniques employed.
   - It provides a foundation for scaling to more complex models or larger datasets if required in the future.
4. **Customizability**
   - The modular workflow allows easy customization of preprocessing steps, feature extraction methods, or machine learning models based on specific requirements or new advancements in the field.
5. **Cost-Effectiveness**
   - The system is designed to minimize computational costs while maximizing output accuracy, making it suitable for deployment in resource-constrained environments.

Discussion :

This study demonstrates that simplicity can yield effective solutions in the field of fake news detection. By focusing on lightweight machine learning models and leveraging TF-IDF for feature extraction, the proposed system achieves a balance between accuracy and computational efficiency. The integration of Google Colab as the computational platform further enhances the system's accessibility, making it a practical solution for researchers and developers with limited resources.This approach contrasts with more advanced methodologies that rely on deep learning or ensemble techniques, which, although accurate, are often computationally prohibitive. The results affirm that careful algorithm selection and preprocessing can deliver impactful results without the overhead of complex models.Future work could extend this methodology by exploring additional features, such as sentiment analysis or user metadata, to enhance classification accuracy further. Additionally, expanding the model to multi-class classification could provide a more granular understanding of misinformation types.

Study	Algorithms Used	Feature Extraction	Strengths	Limitations
IJERT (2020)	Logistic Regression, Naive Bayes, Random Forest	Bag-of-Words, TF-IDF, N-grams	Rich feature diversity; external checks	High computational complexity; generalizability issues
UC Davis (2020)	LSTM, ANN, Logistic Regression	Word2Vec, CountVectorizer	Advanced NLP models; contextual embeddings	Computational resource dependency
Huang (2020)	Naive Bayes, Passive Aggressive, LSTM	TF-IDF, Embeddings	Linguistic focus; balanced complexity	Overfitting risks; platform dependency
Proposed	Logistic Regression, Passive Aggressive	TF-IDF	Simplicity; computational efficiency	Limited feature diversity; fewer models

Conclusion :

The proliferation of fake news necessitates efficient and accessible detection systems to safeguard the integrity of information ecosystems. This study presents a streamlined pipeline that balances simplicity, efficiency, and scalability. By employing lightweight models and focusing on essential preprocessing techniques, the proposed system offers a viable solution for combating misinformation. The use of Google Colab further enhances accessibility and scalability, demonstrating the potential for deploying this approach in diverse operational contexts. Future research could integrate additional features and datasets to extend the system's applicability and robustnes

REFERENCES :

1. Uma Sharma et al., "Fake News Detection using Machine Learning Algorithms," IJERT, 2020.
2. Sairamvinay Vijayaraghavan et al., "Fake News Detection with Different Models," arXiv, 2020.
3. Jeffrey Huang, "Detecting Fake News With Machine Learning," Journal of Physics: Conference Series, 2020.