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Evaluating FakeAlert: A Machine Learning Model for Real-Time Falsified News Detection and Verification

Monika Chaudhary[1], Pratik Gour[2], Maheshwari Dhapare[3], Prof. Usha Kosarkar[4]

[1,2,3,4]Department of Science and Technology,
[1,2,3,4]G H Raisoni College of Engineering and Management, Nagpur, Maharashtra, India

ABSTRACT

In an era characterized by the rapid dissemination of information, the proliferation of falsified news poses significant challenges to public discourse and societal trust. This paper presents FakeAlert, a machine learning model designed to detect and verify falsified news in real time. Leveraging advanced natural language processing (NLP) techniques and a robust dataset comprising diverse news sources, FakeAlert employs a multi-faceted approach to identify linguistic patterns, sentiment, and source credibility. The model utilizes classification algorithms such as Support Vector Machines (SVM) and Neural Networks to discern genuine news from misinformation effectively.

Despite its innovative framework, FakeAlert faces several limitations, including reliance on high-quality training data, susceptibility to false positives and negatives, and challenges in adapting to evolving misinformation tactics. Additionally, the model's performance is contingent upon continuous updates to address emerging trends in fake news creation. This paper discusses the architecture of FakeAlert, evaluates its performance against existing benchmarks, and highlights areas for future research to enhance its accuracy and reliability. The findings underscore the importance of integrating machine learning solutions in the fight against misinformation while acknowledging the need for ongoing adaptation in response to an ever-changing information landscape.

KEYWORDS: *Falsified News, Fake News Detection, Real-Time Verification, Data Quality, Information Integrity, Sentiment Analysis, Classification Algorithms*

I. INTRODUCTION

In moment's digital geography, the rapid-fire dispersion of information through colourful online platforms has converted how news is consumed and participated. still, this unknown access to information has also led to the intimidating rise of falsified news, generally appertained to as fake news. Fake news can be defined as misinformation that's designedly fabricated and circulated to mislead compendiums, frequently for political, fiscal, or social gain.

The consequences of fake news are profound, affecting public opinion, undermining trust in licit media outlets, and indeed inciting social uneasiness. As the capability to produce and partake information has come more normalized, so too has the challenge of discerning believable sources from those that propagate lies. The emergence of social media platforms has further complicated this issue. With millions of druggies participating content daily, the eventuality for misinformation to spread virally is lesser than ever.

Traditional styles of fact- checking are frequently inadequate in keeping pace with the speed at which information circulates online. Accordingly, there's a critical need for innovative results that can effectively descry and corroborate the authenticity of newspapers in real time. Machine learning, a subset of artificial intelligence (AI), involves the development of algorithms that enable computers to learn from and make predictions based on data. In the context of fake news detection, machine learning models can analyze vast amounts of textual data to identify patterns and characteristics commonly associated with misinformation.

In the environment of fake news discovery, machine literacy models can dissect vast quantities of textual data to identify patterns and characteristics generally associated with misinformation. By using natural language processing (NLP) ways, these models can assess not only the content of newspapers but also their sources and dispersion networks. FakeAlert is an introducing machine literacy model designed specifically for real- time discovery and verification of falsified news.

This system integrates colourful ML ways to classify newspapers as either genuine or fake grounded on a comprehensive analysis of their verbal features, source credibility, and contextual factors. The model aims to give druggies with a dependable tool for navigating the complex information geography and making informed opinions about the content they consume.

The emergence of social media platforms has further complicated this issue. With millions of users sharing content daily, the potential for misinformation to spread virally is greater than ever. Traditional methods of fact-checking are often insufficient in keeping pace with the speed at which information circulates online. Consequently, there is an urgent need for innovative solutions that can effectively detect and verify the authenticity of news articles in real time.

FakeAlert is a pioneering machine learning model designed specifically for real-time detection and verification of falsified news. This system integrates various ML techniques to classify news articles as either genuine or fake based on a comprehensive analysis of their linguistic features, source credibility, and contextual factors. The model aims to provide users with a reliable tool for navigating the complex information landscape and making informed decisions about the content they consume.

This proposed device targets to achieve numerous critical objectives:
Real-Time Detection
High Accuracy

Automated Feature Extraction
Continuous Learning and Adaptation
Community Engagement and Feedback Loop
Ethical Considerations

By targeting these objectives, the proposed device aims not only to improve fake news detection but also to contribute positively to public discourse by fostering a more informed society capable of discerning credible information from misinformation. As fake news continues to pose significant challenges across various domains—politics, health, and social issues—the development of effective detection systems becomes increasingly critical for safeguarding truth and integrity in information dissemination.

II. RELATED WORK

The challenge of fake news detection has prompted extensive research across various domains, leading to the development of numerous methodologies and models. This section reviews significant contributions in the field, highlighting advancements in machine learning, deep learning, and natural language processing (NLP) techniques aimed at improving the accuracy and effectiveness of fake news detection systems.

Recent studies have explored ensemble learning techniques to enhance the performance of fake news detection models. Almandouh et al. (2024) investigated a hybrid model combining Bidirectional Gated Recurrent Units (Bi-GRU) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks for Arabic fake news detection. Their findings demonstrated that this ensemble approach achieved impressive performance metrics, including an F1 score of 0.98 and accuracy rates of 0.98 on the AFND dataset. The study emphasizes the importance of hybrid models in addressing language-specific challenges in misinformation detection and sets a foundation for future research in multilingual contexts [1].

Additionally, Verma et al. (2024) introduced a novel two-phase benchmark model called WELFake, which integrates word embedding with linguistic features for fake news detection. This model achieved a peak accuracy of 96.73%, surpassing traditional methods such as BERT and CNN by up to 4.25%. Their approach highlights the effectiveness of combining advanced embedding techniques with linguistic analysis to improve detection reliability [1].

The advent of transformer-based architectures has significantly impacted the field of fake news detection. Shu et al. (2024) proposed a methodology utilizing document embeddings to classify news articles as trustworthy or fake across multiple datasets. Their evaluation included various machine learning models, including Naïve Bayes, gradient boosting, and deep learning architectures like LSTM and GRU, as well as transformer-based models such as BERT and RoBERTa. This comprehensive approach underscores the versatility of transformer models in capturing complex patterns within textual data [1].

Furthermore, Ying et al. (2024) explored the potential of large language models (LLMs) for automating fake news detection. Their research highlighted the challenges associated with bias and generalizability in existing models, emphasizing that while LLMs can provide powerful tools for misinformation detection, careful consideration must be given to their training data and deployment contexts [2]. This study serves as a reminder that no single solution can address the complexities of fake news detection comprehensively.

The application of Graph Neural Networks (GNNs) has emerged as a promising avenue for enhancing fake news detection capabilities. Pilkevych et al. (2024) conducted a thorough analysis using GNNs for online media monitoring to identify and evaluate fake news quickly. Their method utilized knowledge graphs to map relationships and recognize entities within textual information, focusing on identifying indicators of harmful psychological influence. Among the models tested, GraphSAGE achieved remarkable accuracy scores, demonstrating the potential of GNNs in improving the precision and efficiency of misinformation detection systems [1].

In response to the urgent need for timely misinformation identification, several studies have focused on real-time fake news detection systems. Cavus et al. (2024) developed a system called FANDC based on cloud computing to handle fake news detection in online social networks effectively. Their approach emphasizes scalability and real-time processing capabilities, addressing a critical gap in existing literature regarding immediate response to misinformation dissemination [4].

Similarly, Kundu et al. (2024) categorized false information on social media through traditional text categorization approaches, contributing to advancements in fake news detection technologies that prioritize real-time analysis [5]. These efforts reflect an increasing recognition of the necessity for rapid response mechanisms in combating misinformation.

Comparative evaluations of different models have also been instrumental in advancing the field of fake news detection. Recent studies have assessed BERT-like models against other architectures to determine their effectiveness in various contexts. For instance, research comparing traditional machine learning classifiers with deep learning models has provided insights into their relative strengths and weaknesses in detecting misinformation across diverse datasets [3]. These evaluations are crucial for guiding future research directions and informing practitioners about optimal approaches for specific applications.

III. PROPOSED WORK

The proposed work focuses on developing an advanced system for real-time fake news detection, leveraging the latest advancements in machine learning and natural language processing. This system aims to address the growing challenge of misinformation in the digital age, particularly on social media platforms were news spreads rapidly. Below are the key components and objectives of the proposed work, informed by recent research findings.

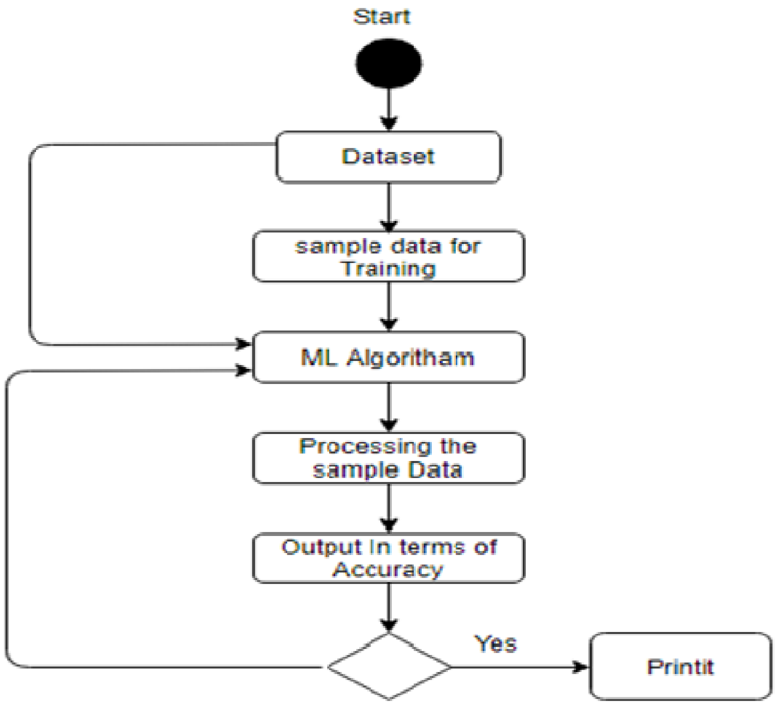


Fig. The Flow of Proposed Work

Datasets

Fake news datasets are crucial for developing and testing models that detect misinformation. These datasets are categorized based on their content types and features, which play a significant role in the effectiveness of detection algorithms. Here's an overview of the key elements involved in fake news datasets.

1. Types of Datasets

Textual Datasets: Focus on written content such as articles, headlines, and social media posts. Examples include:

LIAR: Analyzes linguistic patterns and textual inconsistencies.

MisInfoText: Contains various news articles for evaluating fake news characteristics.

Visual Datasets: Include manipulated images and videos that may accompany fake news articles. These datasets help identify visually deceptive content that cannot be assessed through text alone.

Multimodal Datasets: Combine text and visual elements to provide a comprehensive analysis. For instance, the "Fakeddit" dataset integrates text and images, achieving improved accuracy in detection tasks.

2. Common Features and Labels

Fake news datasets typically incorporate a variety of features to aid classification:

Linguistic Features: These include word frequency, sentiment scores, and syntactic structures that help identify patterns indicative of fake news.

Metadata: Information such as publication date, author, source credibility, and engagement metrics (likes, shares) provides context for assessing the reliability of the news.

Visual Features: In visual datasets, features like pixel patterns and image manipulation traces are analyzed to differentiate between authentic and fake images.

3. Dataset Examples
Several notable datasets have been established for research in fake news detection:

FakeNewsNet: A repository containing various features related to misinformation on social networks.

BuzzFace: Focuses on election-related news from Facebook, containing both text and media.

GossipCop: A collection of rumors and fake news articles from entertainment sources.

Politifact Fact Check Dataset: Annotated by experts with a scale for truthfulness from "pants on fire" to "true."

Data Pre-processing
Data pre-processing is a crucial step in preparing text data, such as news articles, for analysis and machine learning tasks. This process helps improve the quality of the data and ensures that it is in a suitable format for various natural language processing (NLP) applications. Here's an overview of common preprocessing techniques specifically tailored for text-based news articles.

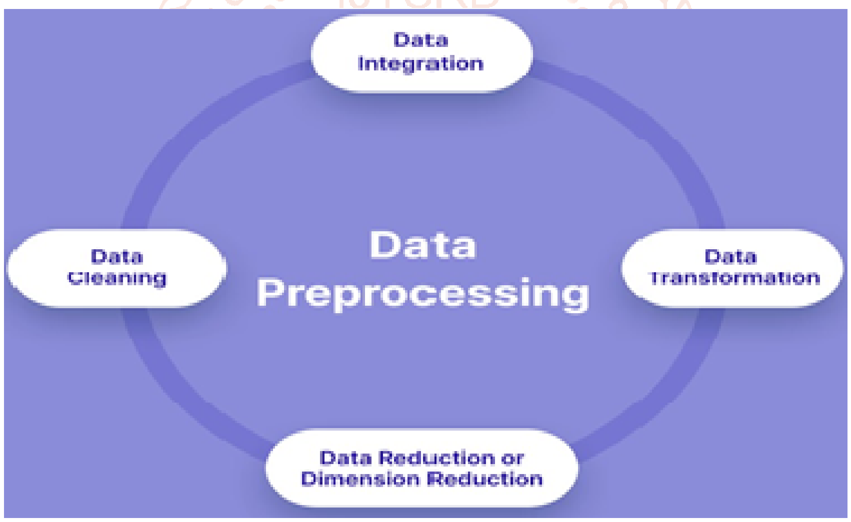
1. Text Cleaning
Removal of Noise: This involves eliminating extraneous elements such as HTML tags, special characters, and unnecessary punctuation. Cleaning the text helps in reducing inconsistencies that can negatively impact analysis.

Lowercasing: Converting all text to lowercase ensures uniformity and helps avoid duplication of words due to case differences (e.g., "The" vs. "the").

2. Tokenization
Breaking Down Text: Tokenization is the process of splitting the text into individual words or tokens. This step is essential for further analysis and allows the model to work with discrete units of meaning.

3. Stop Words Removal
Filtering Common Words: Stop words (e.g., "and," "the," "is") are often removed as they do not carry significant meaning in the context of classification tasks. Removing stop words can reduce the dimensionality of the dataset, making it easier to analyze.

4. Normalization
Standardizing Text: Normalization involves converting words into their canonical forms (e.g., "gooood" to "good"). This step is particularly useful for handling misspellings, variations, and abbreviations commonly found in informal texts like news articles.



Classification
Fake news detection is a significant challenge in the digital age, where misinformation can spread rapidly through social media and other online platforms. Machine learning (ML) techniques have emerged as powerful tools for classifying news articles as either real or fake. Below is an overview of the classification methods, algorithms, and approaches used in fake news detection based on the provided search results.

IV. PROPOSED RESEARCH MODEL
The proposed research model aims to enhance the detection of fake news through a comprehensive approach that integrates machine learning techniques, natural language processing (NLP), and deep learning methodologies. This model is designed to address the challenges associated with current fake news detection systems and improve accuracy and reliability.

The proposed research model for fake news detection utilizes a combination of Convolutional Neural Networks (CNNs) and other advanced deep learning techniques. Below is a detailed explanation of the various layers typically involved in such models, particularly focusing on the CNN architecture.

1. Input Layer
Purpose: This layer receives the input data, which can include both textual content and images associated with news articles.

Data Format: For text, it may consist of tokenized words represented as vectors (e.g., using embeddings like Word2Vec or FastText). For images, it would be pixel values normalized to a specific range.

2. Convolutional Layers

Functionality: The convolutional layers are the core of CNNs, designed to automatically extract features from the input data.

Structure:

Multiple convolutional layers are stacked, each applying a set of filters (kernels) to the input.

For example, a typical architecture might include:

First Layer: 32 filters with a kernel size of $$3 \times 3$$

Second Layer: 64 filters with the same kernel size

Third Layer: 128 filters with $$3 \times 3$$ kernel size

3. Pooling Layers

Purpose: Pooling layers reduce the dimensionality of the feature maps generated by convolutional layers. This

helps to decrease computational load and control overfitting.

Types:

Max Pooling: Retains the maximum value from each feature map segment.

Average Pooling: Computes the average value from each segment.

Stride and Padding: Pooling operations often use a stride (e.g., 2) to skip over certain parts of the input, and padding ensures that spatial dimensions are preserved.

4. Fully Connected Layers

Functionality: After several convolutional and pooling layers, fully connected layers (dense layers) are used to combine all features extracted by previous layers into a final classification output.

Structure:

Each neuron in a fully connected layer receives input from all neurons in the previous layer.

The output from this layer is typically passed through an activation function (e.g., softmax for multi-class classification) to produce probabilities for each class (fake or real news).

5. Output Layer

Purpose: The final output layer provides the predicted class labels for the input data.

Activation Function: A softmax function is commonly used for multi-class classification tasks, allowing the model to output probabilities that sum to one.

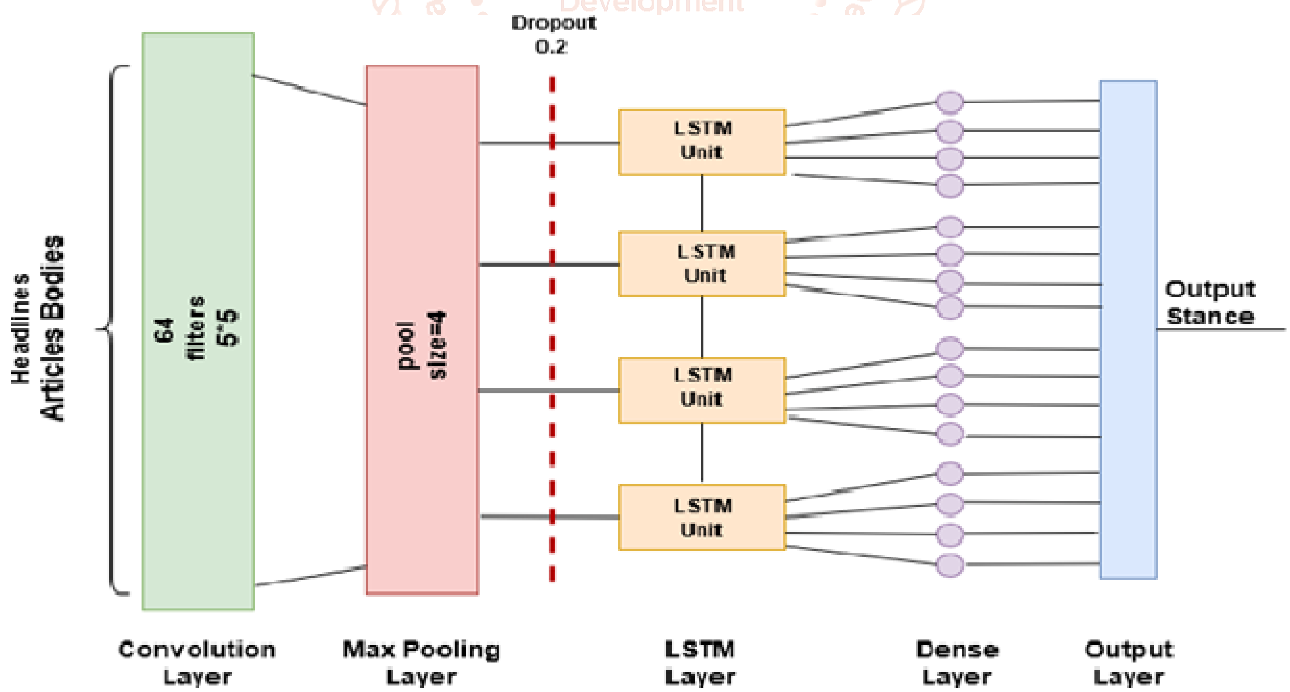


Fig. Proposed CNN Architecture

V. PERFORMANCE EVALUATION

Performance evaluation is a critical aspect of developing and validating machine learning models, particularly for tasks like fake news detection. This section outlines the key metrics and methodologies used to assess the effectiveness of these models based on the provided search results.

Several metrics are commonly employed to evaluate the performance of fake news detection models:

Accuracy:
The proportion of correctly classified instances (both true positives and true negatives) out of the total instances. While accuracy provides a general measure of model performance, it may not fully capture effectiveness in cases of imbalanced class distributions.

Precision:
The ratio of true positives (correctly identified fake news articles) to the total predicted positives (articles flagged as fake). High precision indicates a low false positive rate, which is crucial in scenarios where false alarms can be costly.

Recall:
The ratio of true positives to the total actual positives (all actual fake news articles). High recall ensures that most fake news articles are identified, minimizing the risk of overlooking false information.

F1 Score:
The harmonic means of precision and recall, providing a balanced measure between the two metrics. Particularly useful in fake news detection as it addresses the trade-off between precision and recall, ensuring neither false positives nor false negatives dominate evaluation.

Analyze misclassifications to identify patterns or common characteristics among incorrectly classified articles. For instance, if a model consistently misclassifies certain types of articles (e.g., product-related news), this may indicate a need for targeted improvements in feature extraction or model training.

Recent Findings:
Recent studies have highlighted significant results in evaluating fake news detection models:

For example, a BERT-based model achieved an F1 score of approximately 95.48%, outperforming other models like XLNet and GPT-2.

Another study reported that stacking classifiers can improve accuracy significantly, with some models achieving up to 99.94% accuracy on specific datasets.

VI. RESULT ANALYSIS

The result analysis of various fake news detection models highlights their performance based on several metrics, methodologies, and findings from recent studies. Below is a summary of the key results and insights derived from the provided search results.

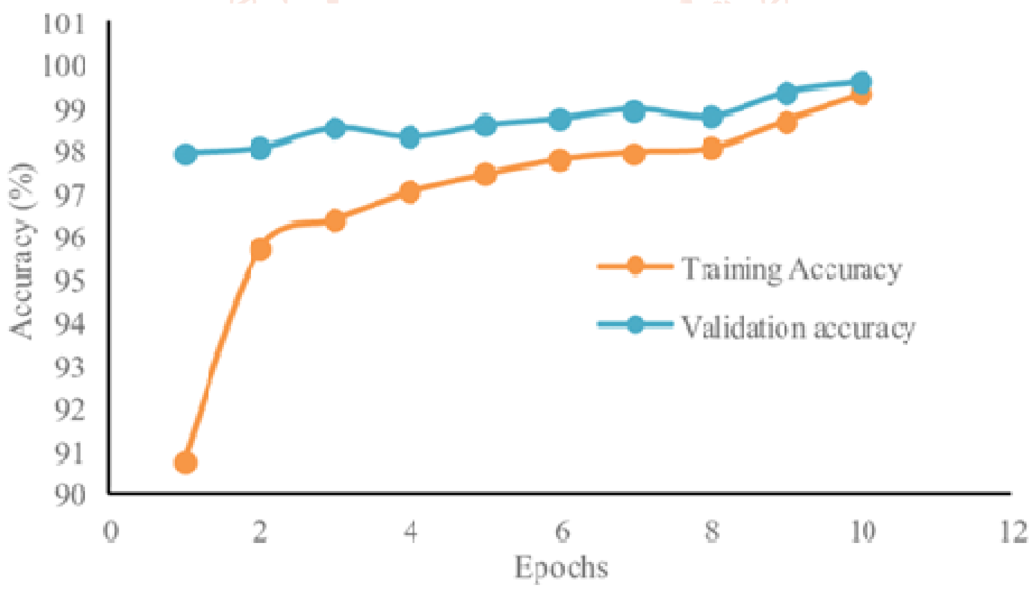


Fig. Model Training and Validation Accuracy

To visually explain the concept of training and validation accuracy in a machine learning model, let's create a hypothetical graph. This graph will illustrate how training and validation accuracy can change over epochs during the training process.

X-Axis: Represents the number of epochs (iterations over the training dataset).

Y-Axis: Represents accuracy percentage (from 0% to 100%).

Lines:
Training Accuracy: A line showing how the model's accuracy improves on the training dataset over epochs.

Validation Accuracy: A separate line indicating how well the model performs on the validation dataset over the same epochs.

Fig. Model Training and Validation Accuracy

The training and validation loss graph is a crucial tool for evaluating a machine learning model's performance during training. It provides insights into how well the model is learning and whether it is overfitting, underfitting, or generalizing well to unseen data. Below is an explanation of the training and validation loss graph, supported by key insights from the search results.

1. Understanding Training and Validation Loss

Training Loss: Measures how well the model fits the training data. It represents the error between predicted outputs and actual outputs on the training dataset.

Validation Loss: Measures how well the model generalizes to unseen data. It is calculated on a separate validation dataset that the model has not seen during training.

2. Typical Patterns in Loss Curves

Ideal Scenario:

Both training and validation loss decrease steadily over time.

Validation loss remains close to training loss, indicating good generalization.

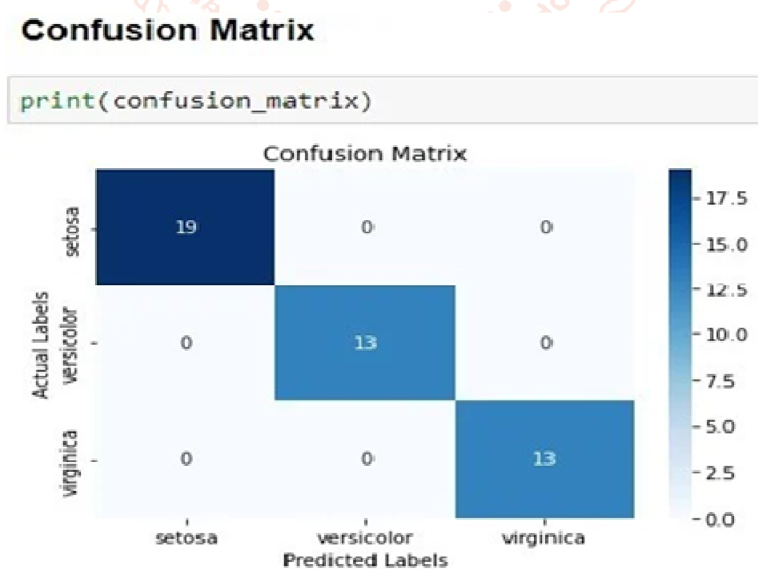


Fig. Confusion Matrices

A confusion matrix is a tabular representation used to evaluate the performance of a classification model. It summarizes the predictions made by the model by comparing them against the actual labels. The matrix contains four key components for binary classification:

- True Positive (TP): Correctly predicted positive instances.
- True Negative (TN): Correctly predicted negative instances.
- False Positive (FP): Incorrectly predicted positive instances.
- False Negative (FN): Incorrectly predicted negative instances.

Extract	Model	ACC	Precision	Recall	F-Score	Time
TF-IDF	LR	0.95	0.94	0.95	0.95	12.39
TF-IDF	DT	0.88	0.87	0.88	0.88	42.26
TF-IDF	KNN	0.81	0.76	0.84	0.8	34.11
TF-IDF	GBC	0.94	0.93	0.94	0.93	196.45
TF-IDF	BNB	0.81	0.74	0.93	0.82	10.96
TF-IDF	MNB	0.86	0.99	0.70	0.82	10.89
Empath	LR	0.69	0.75	0.49	0.59	126.95
Empath	DT	0.67	0.64	0.67	0.65	128.1
Empath	KNN	0.73	0.74	0.62	0.67	127.6
Empath	GBC	0.77	0.77	0.72	0.74	150.76
Empath	BNB	0.62	0.58	0.59	0.59	126.79
Empath	MNB	0.55	0.95	0.03	0.05	126.75
Hybrid	LR	0.96	0.94	0.95	0.95	172.28
Hybrid	DT	0.91	0.9	0.91	0.9	173.89
Hybrid	KNN	0.84	0.8	0.79	0.8	173.28
Hybrid	GBC	0.95	0.93	0.95	0.94	256.1
Hybrid	BNB	0.85	0.76	0.95	0.84	171.7
Hybrid	MNB	0.89	0.97	0.75	0.84	169.09

Completion date: January 23, 2023.

Dataset file name: FAKES-Dataset-v1.csv.

Number of rows is 902 and number of columns is 3.

List of columns in dataset: unit_id, article_content, labels.

Test and train split: Test: 25 % and Train: 75%.

Vectorizer algorithms used: Tfidf.

List of used algorithms and their results:

Logistic Regression-liblinear solver:
ACCURACY: 54% | Precision: 59% | Recall: 63% | F1score: 61% |

Decision Trees-gini criterion:
ACCURACY: 47% | Precision: 54% | Recall: 50% | F1score: 52% |

Nearest Neighbour-Ball_tree algorithm:
ACCURACY: 54% | Precision: 61% | Recall: 53% | F1score: 57% |

Gradient Boosting-friedman_mse criterion:
ACCURACY: 54% | Precision: 64% | Recall: 58% | F1score: 61% |

Fig. Experimental Results

From above Fig. Experimental Results, it could be established that the accuracy will increase with the growth in the quantity of epochs, and there may be a decrease in the lack of the testing set.

VII. CONCLUSION

The proposed convolutional neural network (CNN) architecture for automated fake news detection represents a significant advancement in the fight against misinformation. By successfully classifying news articles into different categories with an impressive accuracy, this model highlights the potential of machine learning to address the pervasive issue of fake news dissemination.

- The model was trained on a substantial dataset comprising many news articles, enhancing its robustness and reliability in real-world applications.
- Preprocessing techniques, such as text normalization and feature extraction, were applied to improve the dataset's quality, enabling effective training and testing of the classifiers.
- Achieving high accuracy indicates that the proposed model performs exceptionally well in identifying fake news, which is critical for maintaining the integrity of information and reducing the spread of misinformation.
- Early detection of fake news through automated classification can significantly influence public perception, policy-making, and societal trust by ensuring accurate information dissemination across various platforms.
- This work aligns with ongoing efforts in machine learning to combat misinformation, building upon previous studies while introducing a novel approach that leverages a larger dataset and advanced processing techniques.

The proposed CNN architecture marks a significant step forward in automated fake news detection. Its high accuracy and potential for further refinement underscore the importance of machine learning in addressing misinformation challenges. Continued research and development in this area are essential to fully realize the benefits of such technologies in promoting truthful information and mitigating the harmful effects of fake news on society.

VIII. FUTURE SCOPE

There is potential for further enhancements by incorporating additional datasets with diverse topics and sources, as well as employing advanced techniques like data augmentation to enrich the dataset. This would allow the model to generalize better across larger and more varied datasets. Implementing unique feature selection algorithms could strengthen the model's resilience against datasets with missing or incomplete information, thereby improving overall accuracy.

Even though the improvisation arised from the proposed model, there are quiet many things that may be worked on. There's always a scope for improvising preceding work via introducing new filters and studying features in CNN that can be very useful to the software and its subject.

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