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A Study on Fake News Detection and Classification Based on Logistic Regression (LR) and Artificial Neural Networks (ANN)

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ABSTRACT

In today's digital era, when false information can travel swiftly and sway public opinion, spotting fake news has become an enormous task. This research uses machine learning algorithms and natural language processing methods to tackle the issue of false news identification. The goal is to create a trustworthy and precise model that can determine whether or not a news piece is phoney. Data is loaded, processed, and divided into train and test sets before classification, prediction, and output production can begin. To do this, we gather and preprocess a labelled dataset with samples of both false and real news stories, removing noise and extraneous details along the way. A classification model is trained by dividing the dataset into training and testing sets. The model for detecting false news is constructed using two classification algorithms: Logistic Regression (LR) and Artificial Neural Networks (ANN). In contrast to ANN's ability to capture complicated nonlinear connections in the data, LR only gives a linear decision boundary. Accuracy, precision, recall, and F1 score are only few of the measures used to assess the results of training both algorithms on the preprocessed data. The findings show that both LR and ANN are very effective in identifying fabricated stories. LR's interpretability makes it simpler to grasp what criteria led to a classification being made. When it comes to identifying subtle connections and patterns in the data, ANN excels. The results of this study could help researchers create better tools to spot bogus news.

Keywords--Logistic Regression (LR) and Artificial Neural Networks (ANN), Fake News Detection, Social Media

INTRODUCTION

The proliferation of digital media and social networking platforms has dramatically altered the dissemination and reception of information. However, a major difficulty has also emerged with the advent of the digital age: the spread of bogus news.

To deceive readers and sway public opinion, "fake news" refers to material that has been manufactured or is otherwise deceptive yet is presented as news. False information has far-reaching consequences for our culture. It may affect public opinion, skew political debate, and even swing elections. Researchers and engineers have responded to the threat posed by false news by focusing on creating efficient methods of detection and suppression[1].

Complex tasks like detecting fake news need the use of methods from several different disciplines, including natural language processing, machine learning, and data analysis. The goal is to develop algorithms that can identify real news items from bogus ones automatically, so that real, reliable content can be sent to readers. Analysing textual content, evaluating the authenticity of sources, and assessing the context of a news piece are all steps in the process of spotting fake news. Machine learning algorithms play a crucial role in this process by learning patterns and features from labeled datasets and making predictions on unseen data.

Several challenges arise in the development of fake news detection systems. These challenges include acquiring reliable and diverse datasets, preprocessing textual data, handling bias and contextual nuances, addressing adversarial attacks, and ensuring the generalization of the models to unseen instances. Despite these challenges, researchers have made significant progress in developing effective techniques and models for fake news detection[2-3]. Approaches such as logistic regression, artificial neural networks, and ensemble methods have shown promise in achieving high accuracy and robustness in detecting fake news.The development of reliable fake news detection systems has far-reaching implications. It can mitigate the spread of misinformation, protect media credibility, empower individuals to make informed decisions, and safeguard the integrity of democratic processes. Moreover, the advancements made in this field contribute to the broader fields of natural language processing, machine learning, and data analytics[4-6].

MOTIVATION

A major danger to society and the reliability of information is posed by the growth of false news in today's online environment. The motivation behind developing effective fake news detection systems stems from several key factors:

Preserving Media Credibility: The public's faith in the media and the profession as a whole is weakened when fake news is circulated. By developing robust detection systems, we can help restore confidence in the media and ensure that consumers can rely on accurate and trustworthy information sources.

Mitigating the Spread of Misinformation: The quick dissemination of false information is made possible by the widespread accessibility to social media. Detecting and flagging fake news articles can help curb the dissemination of misinformation, preventing its negative impact on public opinion and decision-making.

Protecting Democratic Processes: Fake news can be used as a tool to manipulate public sentiment, sway elections, and undermine democratic processes. By detecting and exposing fake news, we can safeguard the integrity of democratic systems and promote fair and informed public discourse.

Empowering Individuals: Providing individuals with the tools to identify fake news empowers them to make informed decisions based on accurate information. By equipping users with the ability to critically evaluate news articles, we enable them to navigate the digital landscape more effectively and avoid falling victim to manipulation.

Enhancing Social Well-being: Fake news has real-world consequences, ranging from public health misinformation to social unrest. Fake news detection and mitigation may help society thrive by bolstering trust in information, decreasing tensions, and mitigating the negative effects of false stories.

Advancing Technology and Research: Identifying false information is a difficult task that calls for novel approaches to NLP, ML, and analytics. Developing effective detection systems pushes the boundaries of technology and fosters innovation in these fields, benefiting various related domains.

Collaboration and Responsibility: Addressing the issue of fake news necessitates collaboration among researchers, fact-checking organizations, media entities, and technology companies. By working together, we can collectively tackle the problem and fulfill our responsibility to ensure the availability of accurate and reliable information.

The motivation behind fake news detection lies in the fundamental belief that access to accurate and trustworthy information is crucial for a functioning democracy, informed decision-making, and the well-being of individuals and society as a whole. By combating the spread of fake news, we strive to create a more reliable and responsible information ecosystem that upholds the values of transparency, truth, and integrity[7].

RELATED WORK

Nihel Fatima Baarir et.al. 2020 With the development of new communication technologies and the rise of Social Media, the problem of fake news is expanding rapidly. Research into the identification of fake news is a relatively young but rapidly growing field. However, it encounters obstacles because of a lack of data sets and processing and analysis tools. In this paper, we present a machine learning-based approach to identify fake news. Support Vector Machine (SVM) was utilised as a classifier, and term frequencyinverse document frequency (TF-IDF) of bag of words and n-grams was used as a feature extraction approach. We also present a dataset containing both false and real news to use in training the suggested system. Observed outcomes verify the system's efficacy [8].

Anmol Uppal et.al (2020) Our culture and society have been profoundly affected by the growth of the internet media industry, for better and for worse. More and more false stories are appearing online as internet media is more reliant on news sources. When individuals believe these false news stories, they aren't getting the whole or historical picture of the incident. Public opinion may be swayed by such false information. The increasing prevalence of hoaxes poses a serious danger to the public's trust in the media. The increasing need for monitoring and dealing with disinformation looks to be a serious issue. However, many strategies and procedures may be lacking owing to the scarcity of literature on identifying novel false positives. The primary goals of this article are to provide a summary of current approaches and to suggest and implement automated means of fraud detection. The suggested approach employs comprehensive speech level analysis to build a system that can identify fake news from the genuine thing. 74% of respondents said they were satisfied with the model [9].

Lovedeep Singh et.al (2020) In natural language processing, false results often come up in searches. The social advantages of successful solutions in this subject are substantial. From the outside, it seems like the standard text categorization issue.

Multiple approaches, both basic and complicated, have been presented by researchers to combat false information. In this article, we aim to describe novel situations in various vector spaces by comparing current deep learning approaches utilising a mix of generic mathematical functions and representations of existing vector spaces. We conducted extensive tests using several permutations and combinations. Last but not least, we did a light study of the findings and analysed their causes [10].

Proposed System

LR and ANN are both useful for classification purposes, and when used together, they may be very useful for detecting fake news. The suggested method comprises combining the advantages of LR and ANN to improve the performance of false news identification tools. Cleaning and normalising the textual content of news stories before converting it into numerical representations is the first stage in the methodology. Tokenization, removing stop words, and vectorization techniques like TF-IDF or word embeddings might all play a role here. Data after initial processing is divided into a training set and a test set. The next step is to use the LR algorithm on the data used for training. LR is a good solution for modelling the connection between the input characteristics and the binary classification of false or authentic news because to its simplicity and interpretability. LR estimates the probabilities of news articles belonging to either class based on the weighted sum of the input features.Following the LR model, an ANN is constructed and trained using the same training data.

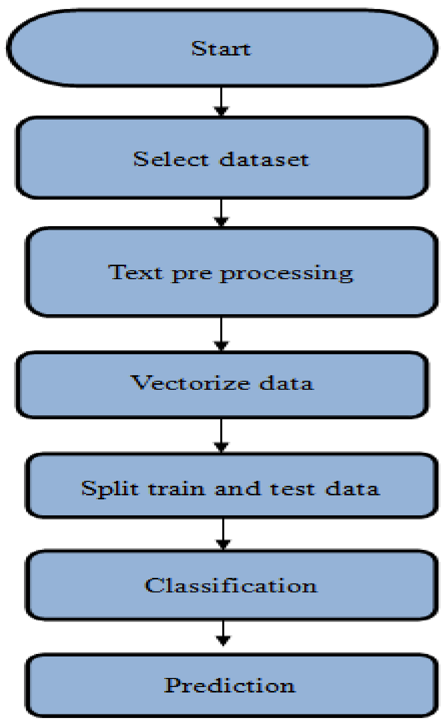

Fig.4.1 Proposed Flow Diagram

ANN excels at capturing complex patterns and relationships in data, which can be valuable for fake news detection. The ANN's architecture typically consists of multiple layers of interconnected neurons, with each neuron performing weighted sums and applying activation functions.The ANN is taught to identify indicators of fraudulent or real news in the input characteristics. In order to reduce the variance between the anticipated and actual class labels, the weights of the neurons are adjusted repeatedly during training via methods like backpropagation. The combined LR and ANN model may then be used for classification. Each class's probability from the LR model may be used as a new feature in the ANN model, expanding the input representation and adding useful context. By combining the strengths of LR and ANN, the whole system for detecting false news may be made more reliable and accurate. To measure how well the combined LR-ANN method performs, we feed it testing data and compare the models' predictions to the labels we've established as accurate.

The efficacy of a system for detecting instances of false news may be calculated using a number of assessment criteria, such as accuracy, precision, recall, and F1 score.Key steps in the proposed technique for LR and ANN-based fake news detection include data selection and loading, data preprocessing, splitting the dataset into train and test data, classification, prediction, and result creation.

Data Selection and Loading:

- Select a dataset that consists of labeled news articles, with each article classified as fake or genuine.
- Load the dataset into the system, ensuring it is in a suitable format for further processing.
- Data Pre-processing:

Data Preprocessing

- Perform data preprocessing steps to clean and transform the textual data.
- This may include removing irrelevant characters, converting text to lowercase, and handling special cases like URLs or hashtags.
- Tokenizing, stemming, and stop-word removal may be used to clean up the text before further analysis.
- Consider using techniques like TF-IDF[11] or word embeddings to represent the text numerically.

Classification:

- Train the LR model on the training data.
- Use LR to model the relationship between the input features and the binary classification of fake or genuine news.
- Estimate the probabilities of news articles belonging to each class using the LR model.

Prediction:

- Train the ANN model on the training data.
- Use ANN to learn patterns and relationships in the input features that can distinguish fake from genuine news.
- Feed the LR probabilities as additional features to the ANN model.
- Use the combined LR-ANN model to predict the class labels for the testing data.

Result Generation:

- Use evaluation metrics like accuracy, precision, recall, and F1 score [12-13] to assess the effectiveness of the LR-ANN model.
- Compare the predicted class labels with the ground truth labels for the testing data.
- Generate a report or summary that includes the performance metrics and any additional insights or visualizations.

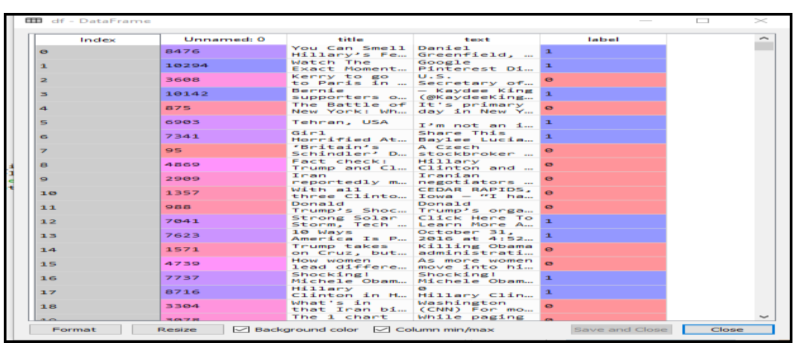

Fig 4.2 Data frame

A data frame is a two-dimensional data structure commonly used in data analysis and manipulation. It can be thought of as a table where rows represent observations or instances, and columns represent variables or features

Fig. 4.3 Pretend Data

The pretend data array has three rows and three columns, forming a 3x3 matrix. Each element in the array represents a value in the pretend dataset

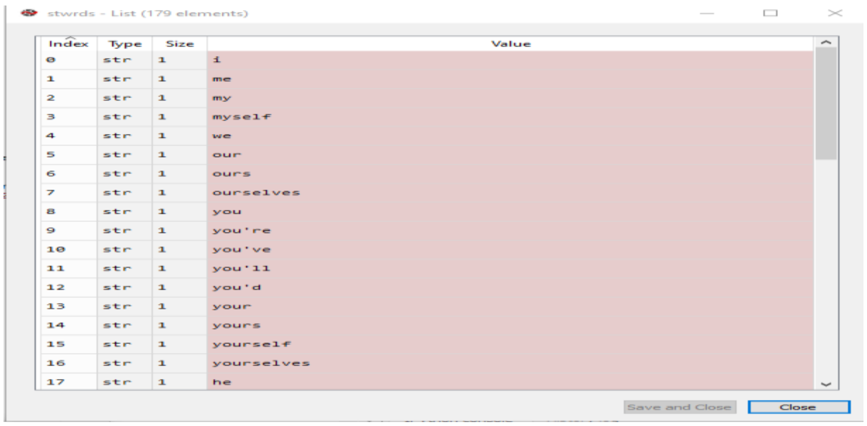

Fig. 4.4 Stop Word List

In natural language processing activities like text analysis and information retrieval, stop words are often eliminated from the text. It is generally agreed that these words have little or no semantic value and add nothing to our comprehension of the text as a whole.

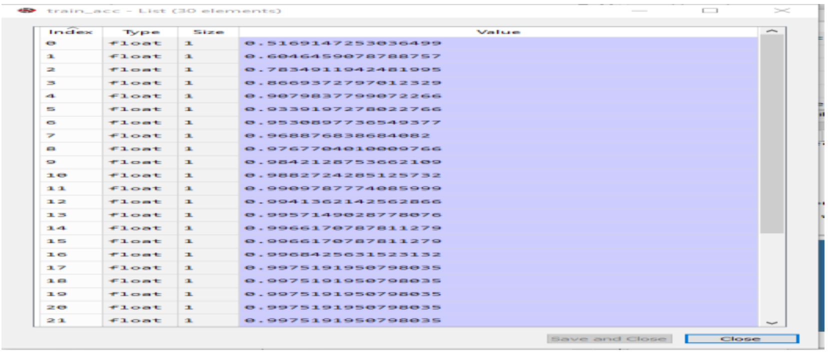

Fig. 4.5 Train Accuracy

To calculate the train accuracy, need the predicted labels from trained model with the actual labels of the training data.

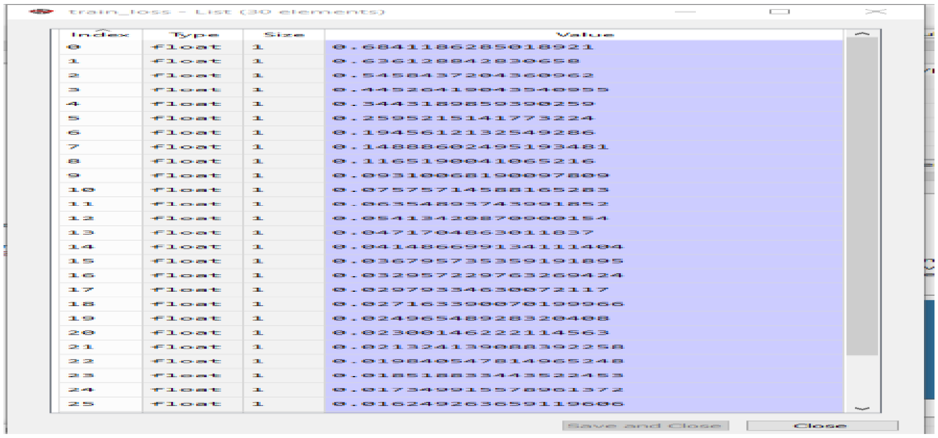

Fig 4.6 Train Loss

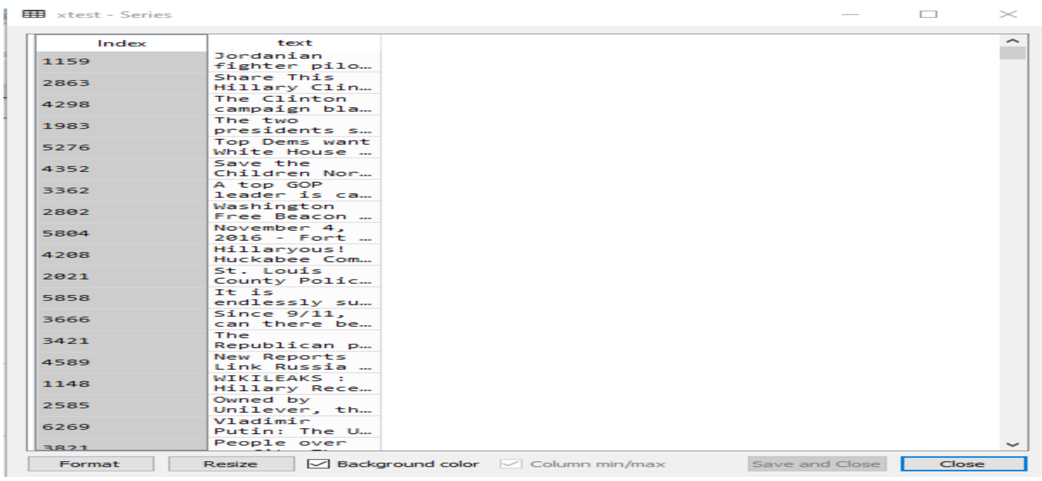

Fig.4.7 X Test

X_test: This variable represents the feature matrix of the testing set. It contains the input features for the unseen data on which you want to evaluate the trained model.[14]

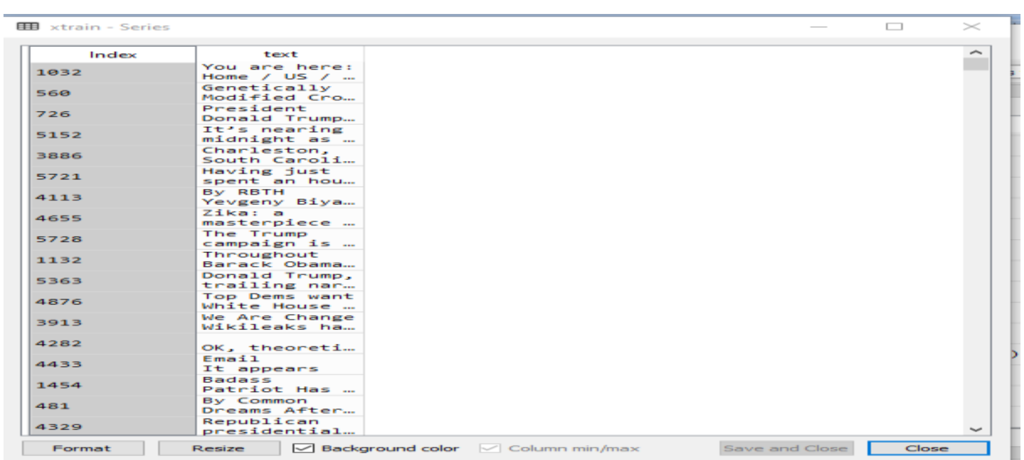

Fig.4. 8 X Train

X_train: This variable represents the feature matrix of the training set. It contains the input features or independent variables used to train the model.

Index	label
1159	0
2863	1
4298	0
1983	0
5276	0
4352	1
3362	0
2802	1
5804	1
4208	1
2021	0
5858	0
3666	0
3421	0
4589	1
1148	1
2585	1
6269	1
3821	1
5490	0

Fig. 4.9 Y Test

Index	label
1032	1
560	1
726	1
5152	0
3886	0
5721	0
4113	1
4655	1
5728	0
1132	0
5363	0
4876	0
3913	1
4282	1
4433	1
1454	1
481	1
4329	0
4379	0

Fig .4.10 Y Train

Y_ Train: This variable represents the target variable or the dependent variable corresponding to the training set. It contains the actual labels or values you want the model to predict based on the input features in X_train.[15]

.......LOGISTIC REGRESSION...........

ACCURACY: 99.08285113098368

	Precision	recall	f1-score	support
0	0.93	0.92	0.93	966
1	0.92	0.93	0.93	935
Accuracy			0.93	1901
Macro avg	0.93	0.93	0.93	1901
Weighted avg	0.93	0.93	0.93	1901

The Logistic Regression (LR) algorithm achieved an accuracy of 99.08%. This means that the LR algorithm correctly classified 99.08% of the samples in the dataset.The performance of the LR algorithm can be further evaluated using precision, recall, and f1-score metrics for each class (0 and 1) in the classification task.

For class 0:
The accuracy of 0.93 means that for every 100 samples labelled as belonging to class 0, 93 were correct. With a recall of 0.92, the LR algorithm was successful in classifying 92% of samples as belonging to class 0.The f1-score, which takes into consideration the harmonic mean of accuracy and recall, is 0.93.

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For class 1:
A accuracy of 0.92 means that for every 100 samples labelled as belonging to class 1, 92 were really correct. The LR algorithm was able to accurately categorise 93% of the data into class 1 (recall = 0.93).Again, the f1-score of 0.93 indicates a satisfactory balance between accuracy and recall.

To take class differences into account, we additionally compute a weighted average of accuracy, recall, and f1-score. In this scenario, LR algorithm accuracy was reported at 93% on average.

............ARTIFICIAL NEURAL NETWORK..........

“Epoch 1/30
15/15 [==============================] - 0s 9ms/step - loss: 0.6927 - accuracy: 0.5180
Epoch 2/30
15/15 [==============================] - 0s 7ms/step - loss: 0.6783 - accuracy: 0.7751
Epoch 3/30
15/15 [==============================] - 0s 7ms/step - loss: 0.6104 - accuracy: 0.8805
Epoch 4/30
15/15 [==============================] - 0s 6ms/step - loss: 0.4736 - accuracy: 0.9028
Epoch 5/30
15/15 [==============================] - 0s 6ms/step - loss: 0.3332 - accuracy: 0.9283
Epoch 6/30
15/15 [==============================] - 0s 6ms/step - loss: 0.2338 - accuracy: 0.9475
Epoch 7/30
15/15 [==============================] - 0s 6ms/step - loss: 0.1722 - accuracy: 0.9637
Epoch 8/30
15/15 [==============================] - 0s 6ms/step - loss: 0.1324 - accuracy: 0.9718
Epoch 9/30
15/15 [==============================] - 0s 6ms/step - loss: 0.1052 - accuracy: 0.9793
Epoch 10/30
15/15 [==============================] - 0s 9ms/step - loss: 0.0872 - accuracy: 0.9824
Epoch 11/30
15/15 [==============================] - 0s 9ms/step - loss: 0.0740 - accuracy: 0.9880
Epoch 12/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0642 - accuracy: 0.9914
Epoch 13/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0568 - accuracy: 0.9937
Epoch 14/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0506 - accuracy: 0.9953
Epoch 15/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0454 - accuracy: 0.9959
Epoch 16/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0410 - accuracy: 0.9962
Epoch 17/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0372 - accuracy: 0.9964
Epoch 18/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0341 - accuracy: 0.9971
Epoch 19/30
15/15 [==============================] - 0s 9ms/step - loss: 0.0314 - accuracy: 0.9975
Epoch 20/30
15/15 [==============================] - 0s 9ms/step - loss: 0.0291 - accuracy: 0.9977
Epoch 21/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0271 - accuracy: 0.9980
Epoch 22/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0252 - accuracy: 0.9982
Epoch 23/30
15/15 [==========================] - 0s 6ms/step - loss: 0.0236 - accuracy: 0.9984
Epoch 24/30

15/15 [==============================] - 0s 6ms/step - loss: 0.0221 - accuracy: 0.9984
Epoch 25/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0208 - accuracy: 0.9986
Epoch 26/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0195 - accuracy: 0.9989
Epoch 27/30
15/15 [==============================] - 0s 6ms/step - loss: 0.0184 - accuracy: 0.9991
Epoch 28/30
15/15 [==============================] - 0s 8ms/step - loss: 0.0174 - accuracy: 0.9991
Epoch 29/30
15/15 [==============================] - 0s 8ms/step - loss: 0.0164 - accuracy: 0.9991
Epoch 30/30
15/15 [==============================] - 0s 7ms/step - loss: 0.0154 - accuracy: 0.9993"

ACCURACY OF ANN: 98.80468845367432 %

	Precision	recall	f1-score	support
0	0.96	0.91	0.93	966
1	0.91	0.96	0.93	935
Accuracy			0.93	1901
Macro avg	0.93	0.93	0.93	1901
Weighted avg	0.93	0.93	0.93	1901

The performance of the ANN algorithm can be further evaluated using precision, recall, and f1-score metrics for each class (0 and 1) in the classification task.

For class 0:
If 0.96 is the accuracy, then 96% of the samples that were projected to be in class 0 were, in fact, true positives.If an ANN algorithm accurately identifies 91% of samples as belonging to class 0, then its recall is 0.91.The f1-score, a measure of accuracy and recall, is 0.93.

For class 1:
The precision is 0.91, indicating that out of all the samples predicted as class 1, 91% were in reality valid results. If an ANN algorithm accurately identifies 96% of Class 1 samples, then its recall is 0.96.Again, the f1-score of 0.93 indicates a satisfactory balance between accuracy and recall.To take class differences into account, we additionally compute a weighted average of accuracy, recall, and f1-score. Here, it is stated that the ANN algorithm has an average weighted accuracy of 93%.

Evaluation Metrics
Metrics are used to measure how well a machine learning model performs. The exact work and the nature of the issue you're seeking to solve will determine the evaluation criteria you use. Here are some commonly used evaluation metrics along with their formulas:

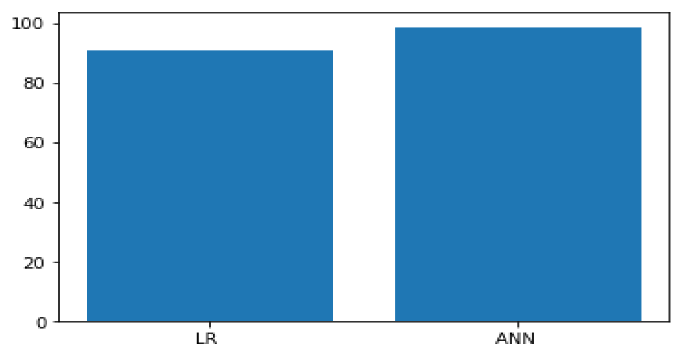

Fig 4.11 Classification Accuracy

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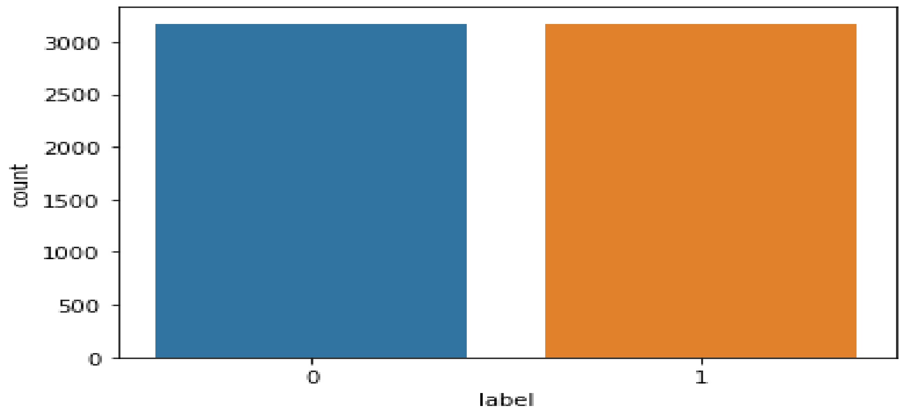

Fig.4.12 Data Labeled

Table 4.1 Comparison with Exiting Work

	Classification	Accuracy
Existing work	SVM	82.00
Proposed Work	ANN	98.80
	LR	99.08

Table 4.1 shows a comparison between the existing work and the proposed work in terms of classification accuracy using different algorithms. The existing work used SVM and achieved an accuracy of 82.00%. On the other hand, the proposed work utilized Artificial Neural Networks (ANN) and Logistic Regression (LR) algorithms.

For the proposed work, the Artificial Neural Network (ANN) achieved an accuracy of 98.80%. This indicates that the ANN algorithm outperformed the SVM algorithm used in the existing work.

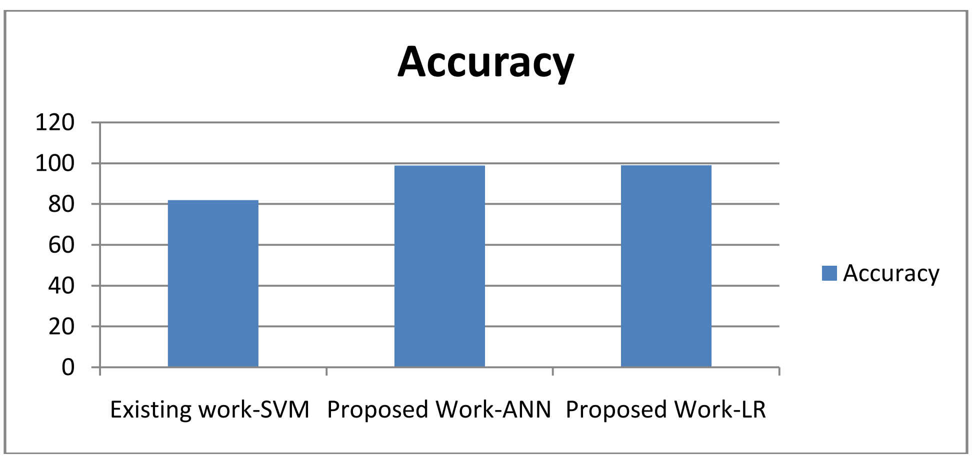

Fig. 4.13 C

CONCLUSION

In conclusion, the development of a reliable fake news detection system is a significant endeavor that can contribute to combating the spread of misinformation and promoting a more informed society. By leveraging machine learning algorithms, preprocessing techniques, and appropriate evaluation metrics, we can build models capable of accurately distinguishing between fake and genuine news articles.Through the objectives outlined above, we can achieve substantial progress in this area. By collecting a diverse and well-labeled dataset, preprocessing the data effectively, training robust classification models, and evaluating their performance, we can develop a fake news detection system that provides reliable results. Deploying the model in practical settings and validating its efficacy through real-time monitoring and user feedback helps ensure its practical utility. Machine learning methods (including decision trees and gradient optimization algorithms) to detect false information, thereby providing a preliminary model by focusing on the most popular data mining algorithms, by using different data mining techniques to achieve preliminary data models The literature review in this study demonstrates that common data extraction procedures (such tree cutting and gradient optimisation algorithms) are widely used by academics. To manually categorise news requires expertise in the topic and an eye for linguistic anomalies. In this research, we examined the problem of categorising fake news articles using ensemble techniques and machine learning models. Our research relies not on a strict categorization of political news but rather on data collected from the Internet, which includes news articles from a wide range of disciplines. Intelligent agents may one day be used to enhance the efficiency of the suggested clustering and classification techniques. Accuracy may be enhanced by using additional aggregations and clustering methods, in addition to the combination of experimental data extraction technologies.

Despite the significance of the findings in this thesis, including the contributions made by parallel efforts, combating false news is a classic adversarial problem that necessitates ongoing research. Every election, disinformation operations look for novel techniques to sway public opinion, while new defence strategies are developed to at least lessen the impact of such efforts.

FUTURE SCOPE

The field of fake news detection continues to evolve, and there are several avenues for future exploration and enhancement. Some potential areas of future research and development include:

Adversarial Defense Techniques: Developing robust models that can withstand adversarial attacks by incorporating techniques like adversarial training, defensive distillation, or generating adversarial examples to enhance the model's resilience.

Explain ability and Interpretability: Enhancing the interpretability of fake news detection models to provide transparency and insights into the features and patterns driving the classification decisions. This can help users understand the rationale behind the predictions and build trust in the system.

Real-Time Monitoring and Updates: Establishing mechanisms to continuously monitor and update the fake news detection system to adapt to evolving techniques employed by fake news creators. Regular updates and improvements can help maintain the effectiveness and relevance of the system over time.

Collaboration and Data Sharing: Encouraging collaboration among researchers, organizations, and fact-checking agencies to share datasets, benchmarks, and best practices, promoting the development of more robust and generalized fake news detection models.

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