UNIVERSITY of BRADFORD
Faculty of Engineering & Informatics

MSc Artificial Intelligence

DETECTION OF FAKE NEWS USING MACHINE LEARNING ALGORITHMS

Advanced Machine Learning

SUBMITTED BY

Name: Jammal Adeyemi
UB Number: 21032609

SUBMITTED TO

Dr Paul Trundle

May 2023

ABSTRACT

Fake news has become a major problem in recent years, particularly with the proliferation of social media and online news sources. Detecting false information is challenging due to the widespread distribution of disinformation, propaganda, and altered content. In this study, we evaluate the effectiveness of various algorithms and techniques for identifying fake news. We conduct a critical analysis of publicly available datasets that contain both genuine and fraudulent news stories. Our proposed approach utilizes several machine learning algorithms, including Logistic Regression, Random Forest, Naive Bayes, Gradient Boosting Classifier, Decision Tree Classifier, and Extreme Gradient Boosting. We use a range of datasets, including those from the Hugging-face dataset library and Kaggle, and label the news articles as either fake or real (0 or 1). Our findings demonstrate that these models can accurately classify news articles into legitimate and fraudulent sources, with classification accuracy scores of up to 99%. We acknowledge the limitations of our study and offer suggestions for further research. Our study contributes to the ongoing efforts to combat fake news by analyzing research in detecting fake news and identifying the most effective machine learning model. We propose a supervised learning algorithm, using Python scikit-learn and NLP techniques for textual analysis, to categorize news articles as either real or fake. Our proposed method involves feature extraction and vectorization of text data, utilizing tools such as Count Vectorizer and Tiff Vectorizer from the Python scikit-learn package. We conduct feature selection techniques to identify the most appropriate features to achieve maximum accuracy based on the confusion matrix analysis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

There have been many cultural shifts due to the internet's rapid transformation of our communication landscape. Regarding regular communication, social media is widely regarded as the gold standard. The lives of people of all ages, from the youngest to the oldest, have been profoundly altered by the advent of social media. As a result, people are more likely to pass forward what they read on social media without verifying its integrity, thanks to the widespread usage of these platforms. People need to verify its integrity before spreading information. There are wide varieties of fake news; some intentionally mislead their audience by playing on their passions and sharing them on social media. In addition to viral messages spread across several social media platforms without anybody evaluating their veracity, phone headlines have been made to show fabricated facts (Huang, 2017).

In today's media environment, where consumers are producers, false information spreads like wildfire. Anyone may apply incorrect statements on social media. The primary goal of these fake news producers is to deceive news consumers. This news aims to achieve some end, such as sowing discord in the community or smearing someone's or some group's reputation. Therefore, the ability to spot propaganda and evaluate news credibility is more important than ever. People need to verify the legitimacy of news articles before sharing them (Howard, 2017). Therefore, this is a crucial feature that might limit the dissemination of private data. Identifying fake news helps determine the integrity of information transmitted on the internet. We employ two freely available online datasets to evaluate these strategies, the Kaggle online dataset and the HuggingFace dataset library.

This study aims to develop a high-performance AI model for identifying fake news, using techniques such as traditional machine learning, and Deep-Learning.

1.1 PROBLEM STATEMENTS

The expeditious metamorphosis of the communication realm brought about by the internet has brought about significant cultural transformations, particularly in terms of social media as the primary avenue for communication. Regrettably, false information disseminates rapidly through these platforms owing to the absence of verification of its authenticity. The ubiquitous use of social media has heightened the proclivity of individuals to disseminate unverified information, resulting in the propagation of false information. This type of information can be deliberately deceptive and used to hoodwink news consumers, create discord within the community, or besmirch the reputation of individuals or groups. The insufficiency of mechanisms to identify and authenticate the legitimacy of news articles has given rise to the widespread prevalence of false information. To address this predicament, the research proposes a supervised machine learning model with high-performance metrics to effectively recognize counterfeit news and curtail the spread of false information.

1.2 PROJECT AIM AND OBJECTIVES

The aim of this project is to develop a precise and dependable ML model that can effectively classify news articles into two categories: real or fake. To achieve this, the study has laid out a set of objectives, which are as follows:

- Collect and preprocess labelled news datasets, incorporating various news sources and subjects, to generate a comprehensive dataset that is representative of a diverse range of news articles.
- Utilize NLP techniques, such as tokenization, lemmatization, and stop-word removal, to preprocess the textual data and extract relevant features that can be used for classification.
- Implement traditional ML algorithms, such as Logistic Regression, Random Forest, and Gradient Boosting Classifier, to train and evaluate their performance on the generated dataset in terms of accuracy, precision, recall, and F1 score.
- Develop a Bidirectional LSTM model and compare its performance with traditional machine learning models.
- Save the best-performing model and test it on unseen news text to evaluate its performance in a real-world scenario.

1.3 REPORT STRUCTURE

This report is organized as follows. Section 2 provides a comprehensive literature review of existing algorithms and methods for fake news detection. Section 3 describes the datasets used in this study and presents the methodology process. Section 4 presents the results of our study, including a detailed analysis of the performance of different machine learning models and techniques. Section 5 provides a critical review and LSEPI relating to our study. Finally, section 6 summarizes our findings, limitations, and recommendations for future research.

To preprocess different labelled news datasets and combine them into one dataset for analysis.

CHAPTER TWO

LITERATURE REVIEW

2.1 GENERAL OVERVIEW

In this age of social media and instant information dissemination, detecting fake news has become a momentous challenge. Machine learning algorithms, by scrutinizing a plethora of news item traits, have proven to be an effective solution to this conundrum.

The "Information Manipulation Theory" is one idea that has been extensively studied in the context of identifying false news using machine learning algorithms. Wu et al. (2018) put out the hypothesis that false news is concocted and spread deliberately to influence public opinion and deceive readers. Sensationalism, emotional appeals, and incorrect information are only some of the tactics used by those with agendas to influence the public, according to this notion. The idea of fake news has been around for a while, but the word got a lot of support during the 2016 US Presidential Elections. The term "fake news" is used to describe tales that are not true but are presented as "news" with the goal of fooling the audience. The widespread dissemination of false information thanks to social media and the internet is a major problem for the news industry, elected officials, and the general public. Motives for fabricating news include financial gain (by readership or ad impressions), political gain, or public opinion manipulation. Fake news has the potential to incite violence, influence political decisions, and harm reputations, all of which are serious repercussions.

Numerous individuals are working on fixing the issue of fake news. To combat the dissemination of false information, social media platforms have implemented fact-checking tools and removed fake accounts and content. Governments and media outlets have launched campaigns to educate the public on recognizing and avoiding deception by fake news.

2.2 TECHNICAL OVERVIEW

Various machine-learning algorithms and techniques have been developed to detect and categorize news stories as authentic or fraudulent. (Gupta et al., 2022) proposed a technique that categorizes news stories based on content and user engagement, while (Chattopadhyay et al., 2023) suggested a method that categorizes tweets according to the origin and how they spread via the social network. Additionally, network analysis has been used to identify bogus news, as demonstrated by (Xu et al., 2021), who proposed a graph-based approach to analyze the social network of news stories and spot suspicious patterns of diffusion. (Kiran et al.,

2023) analyzed the linguistic and social features of fake news and found that it tends to have a lower readability score and uses more emotional language than real news.

(Hiramath and Deshpande, 2021) presented a system for detecting fake news using deep learning techniques. They employed various classification methods such as logistic regression, naive Bayes, support vector machines, random forests, and deep neural networks. The authors evaluated the performance of these algorithms in terms of time, memory, and accuracy, and concluded that the deep neural network algorithm outperforms the other classifiers as it provides more accurate results in less time. (Bhardwaj et al., 2023) experimented with various approaches to detecting and countering false news, including support vector machines, naive-based classifiers, natural language processing techniques, sentence similarity, and classification algorithms. They proposed a data mining strategy to identify social media-based false news, taking into account the publisher, content, timing of publishing on social networking networks, and the number of interactions amongst various people.

(Saxena et al., 2022) presented a machine-learning model for spotting fake news using feature extraction and linguistic analysis of news articles. They demonstrated that their proposed framework, which uses supervised machine learning techniques such as naive Bayes classification and support vector machines and natural language processing, could reach up to 93.5% accuracy in identifying fake news. Similarly, (Choudhary et al., 2023) proposed a model for identifying suspicious news that makes efficient use of phrase matching via the retrieval of the main text using bidirectional machine-learning techniques. They used various machine learning techniques, such as the naive Bayes classifier, the passive-aggressive classifier, and the deep neural network, and employed the TF-IDF vectorizer to transform the text data included in news stories into its numerical form.

In conclusion, the detection of fake news is a challenging task, and various ML techniques have been developed to tackle this issue. These techniques include classifying news articles based on their content and audience engagement, scrutinizing the social network where the articles are distributed, analyzing the linguistic and social characteristics of counterfeit news, and utilizing advanced deep learning techniques to unearth spurious news.

CHAPTER THREE

METHODOLOGY

For spotting fake news, numerous algorithms and techniques have been developed. Using machine learning algorithms to categorize news stories as authentic or fraudulent is a prevalent strategy. According to the way Wang et al. (2018) suggested, news stories can be categorized based on their content and user engagement using a deep learning model. Another strategy to spot fake news is to examine the news's source and the social network surrounding it (Vosoughi et al., 2018). They suggested a technique that categorizes tweets according to their origin and how they spread via the social network using a deep learning model.

3.1 DATA SCIENCE SYSTEM ARCHITECTURE

The overall process for developing and optimising the AI system for fake news detection consists of several key steps, as illustrated in Fig 3.1. These steps include data ingestion, data & text preprocessing, EDA, modelling, model evaluation, and saving the top-performing model. In the following sections, we will describe each step in more detail and discuss the specific techniques and methods used in our study.

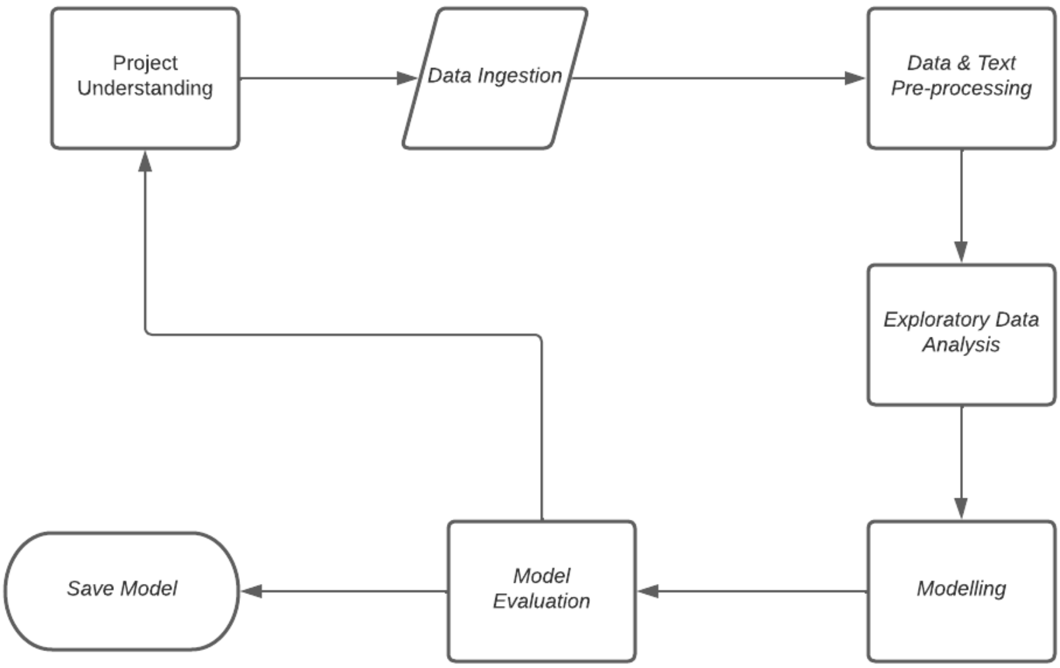

Fig 3.1: AI Workflow

3.1.1 DATA INGESTION

For this project, I have utilized two datasets to perform my analysis. The first dataset was obtained from Hugging Face, a platform that provides access to a diverse range of natural language processing (NLP) datasets curated by Noah Gift. The dataset contains 12 rows and 2096 columns, with only four rows being pertinent to the task at hand. The second dataset was obtained from Kaggle, a platform for data science enthusiasts. The dataset was curated by Clément Bisaillon and contained 4 rows and 44,898 columns. Both datasets were combined to create a comprehensive collection of fake and real news articles for training and testing the model. The dataset contains a total of 4 rows and 46,994 columns, where each row represents an article, and the columns contain various features, such as the article's title, content, and labels (i.e., fake or real).

3.1.2 DATA & TEXT PREPROCESSING

Before training the model, the data needed to be prepared to ensure it was in a suitable format. First, duplicated observations were removed from the dataset, followed by dropping any missing values.

- **Lowering the text**

The 'original' feature, containing the combined text from the 'title' and 'text' features, was converted to lowercase. Converting text to the same case, ideally lowercase is a popular first step in preparing text in Python. However, this is only sometimes a required step when fixing an NLP issue, especially if lower casing causes data loss.

- **Tokenization**

At this stage, the text is divided into smaller portions. Depending on the nature of the issue, we may choose to utilize either phrase tokenization or word tokenization but I decided to stick with word tokenization.

- **Stop words removal**

In order to improve the quality of the analysis, frequently used terms (stop-words) are eliminated from the text. The NLTK library includes a dictionary of regularly used English "stop words." During text preprocessing, popular terms that do not contribute significantly to the text's meaning are eliminated to decrease the text corpus size and boost the algorithm's accuracy. These predetermined stop words may only sometimes be enough for a given activity, which is why I compiled a more extensive list of potential omissions (Russakovsky, 2015).

- **Lemmatization**

The tokens were lemmatized using the WordNetLemmatizer from the nltk library. "lemmatization" refers to a natural language processing approach that breaks down words into their base or dictionary forms. The lemma of the verb "running" is "run," whereas the lemma of "mice" is "mouse." It attempts to classify similar word forms into a single entity for the sake of study.

- **Removing punctuation**

Finally, punctuation marks were removed using the RegexpTokenizer. This process involves erasing all punctuation marks from the text. Some punctuation marks, such as "!"#$ %&'()*+,-. /:;? @ [] _'|," are already defined in Python's string library.

3.1.3 EXPLORATORY DATA ANALYSIS

The news dataset contains 46994 observations and five features. The features are "title," "text," "subject," "label," and "original." The feature "title" represents the title of the news article, and "text" represents the main text of the news article. The "subject" feature represents the news article's subject or category, such as politics, entertainment, and technology. The feature "label" is the target variable, with classes "fake" and "real." Finally, the feature "original" is a concatenation of the "title" and "text" features. The target variable was slightly imbalanced, with 24,775 fake news articles and 22,218 real news articles. This was visualized using a count plot that showed the frequency of each class in the dataset.

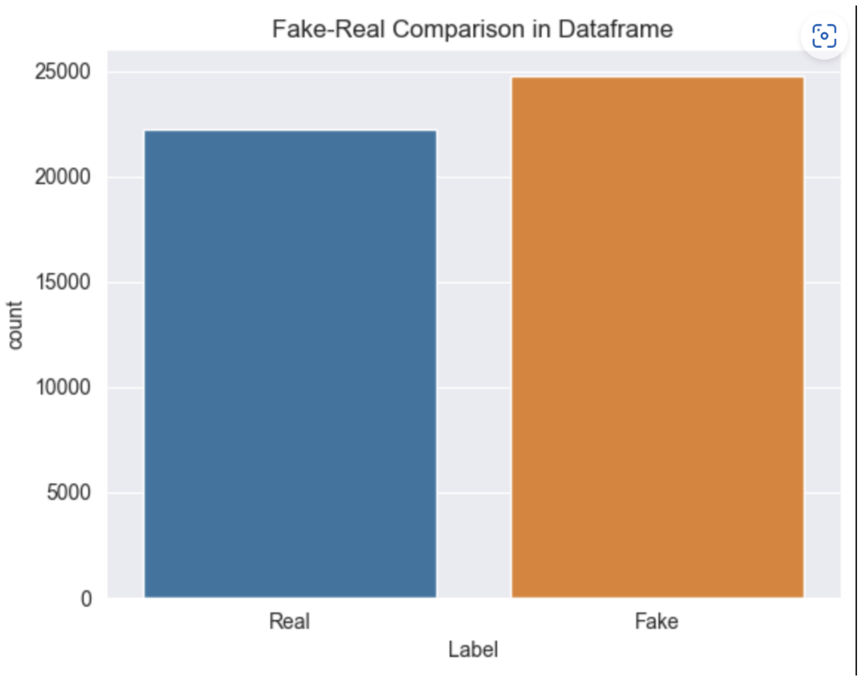

Fig 3.1.1: Fake-Real News Comparison in the Datasets

In terms of the "subject" feature, the most common categories were PoliticsNews (18,113 observations), Worldnews (10,145 observations), and News (9,050 observations). The remaining categories had a much lower number of observations.

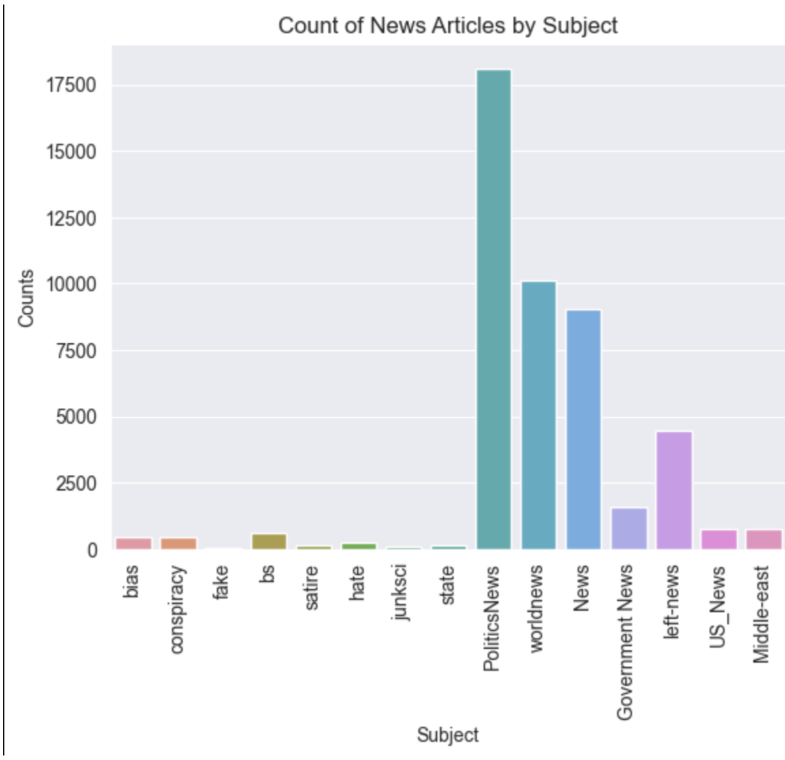

Fig 3.1.2: Counts of News Articles by Subjects

To explore the relationship between the "subject" and "label" features, a count plot was generated, showing the frequency of each category by label (fake or real). The plot revealed that PoliticsNews and Worldnews had a higher percentage of fake news articles, while News, Leftnews, and PoliticsNews had a higher percentage of real news articles.

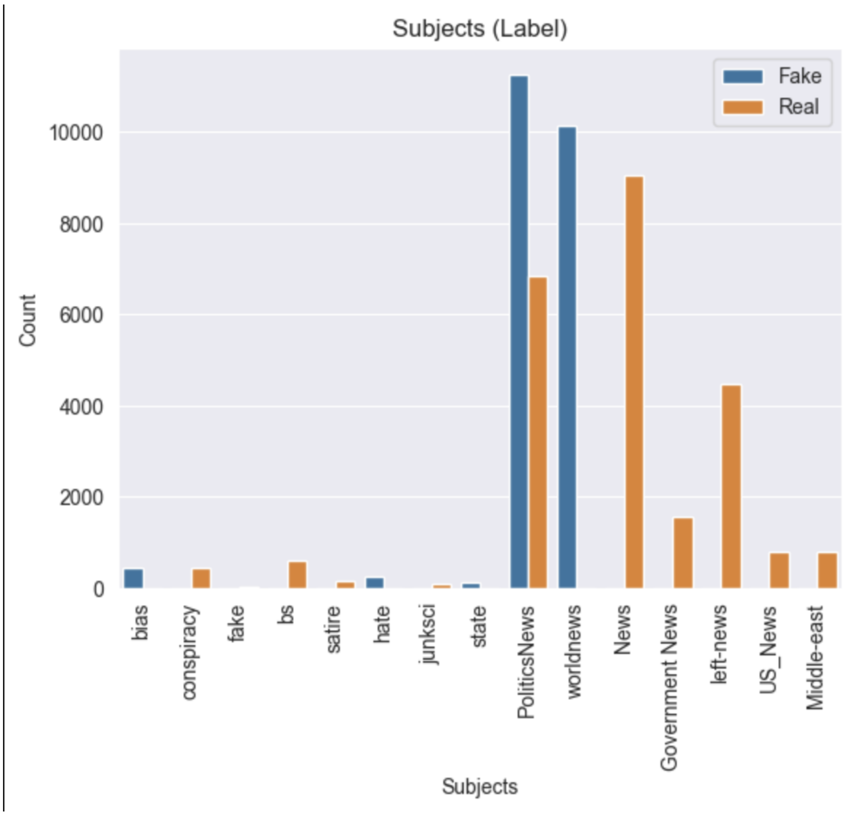

Fig 3.1.3: Subject relating to real&fake news

Overall, these initial analyses provided valuable insights into the distribution of the target variable and the relationship between the "subject" and "label" features, which will guide further exploratory data analysis and model development.

- **DATA ANALYSIS AND VISUALIZATION**

To gain insights into the data, the most common words were visualised using word clouds for real and fake news articles. Words such as "Trump," "president," "said," "state," "people," "us," and "year" were commonly seen in real news pieces, whereas "Trump," "Hillary," "Clinton," "election," "president," and "white house" were common in counterfeit news pieces. However, the study found no significant difference between the two sets of words, indicating that fake news articles used similar language to real news articles.

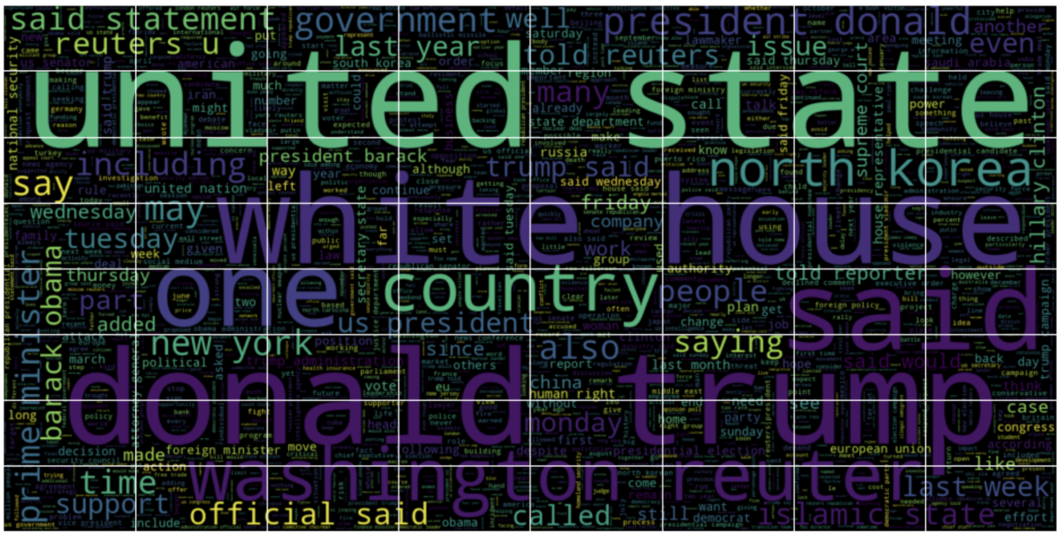

Fig 3.5: Common words from the real news content

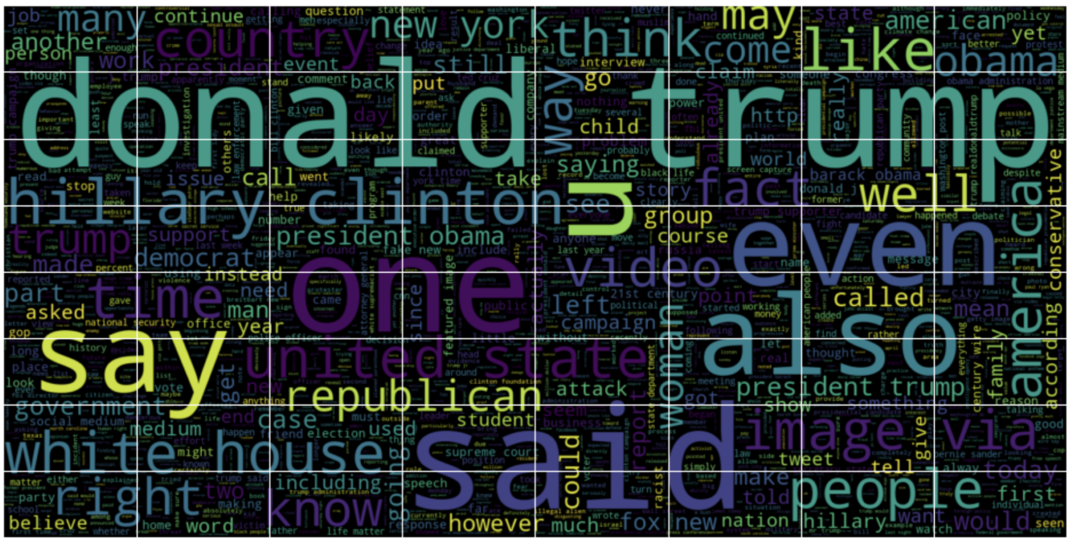

Fig 3.1.4: Common words from the fake news content

Real news articles usually report impartial facts and offer an analysis based on evidence, rather than employing emotionally charged vocabulary or promoting a particular political agenda. Therefore, the prevalent words found in real news articles might include neutral or descriptive phrases linked to the topic at hand, as well as quotations from sources and statements from officials. In contrast, fake news articles often employ emotionally charged terms, hyperbole, and sensationalism to grab the reader's attention and promote a particular political agenda. Some examples of commonly used terms and phrases in counterfeit news content include "shocking," "outrage," "explosive," "scandal," "bombshell," "conspiracy," "cover-up," "hoax," "lies," "deception," "secret," "exposed," "unbelievable," "controversial," and "corruption." These words are frequently utilized in fake news headlines and articles to create a sense of urgency and fascination, and to appeal to the reader's emotions rather than their reason or critical thinking abilities.

Unfortunately, fake news stories have spread rapidly over social media in recent years, causing harm and misleading many individuals. Examples include Pizzagate, where a fake news story claimed that Hillary Clinton and other high-ranking officials were operating a child sex trafficking ring out of a pizzeria in Washington D.C. Another example is a video that circulated on social media, claiming to show migrants burning the French flag in Calais, which was later discovered to be false. During the 2017 hurricane season, several fake news stories circulated on social media claiming that sharks were swimming in the floodwaters and that a chemical plant had exploded, both of which were untrue. False allegations of widespread voter fraud during the 2016 election fueled a narrative that the election was being rigged. Finally, during the COVID-19 pandemic, many fake news stories and conspiracy theories circulated on social media, including claims that the virus was a hoax, that it was created in a laboratory, and that it could be cured with various unproven remedies.

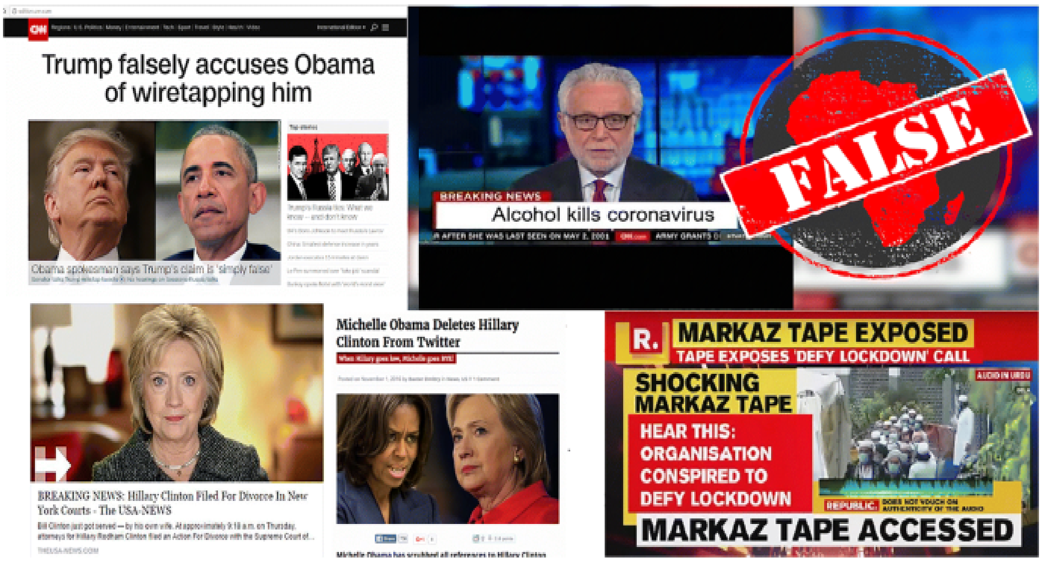

Fig 3.1.5: Examples of some fake news spread over social media

Fake news articles often use sensational or exaggerated headlines, lack credible sources, contain false information, use emotional language and exaggeration, and target readers who have a pre-existing belief or opinion on a specific topic. It is crucial to verify the information before sharing it with others and be critical of the news you read online. Fact-checking websites like Snopes, FactCheck.org, and PolitiFact can be useful resources in identifying and debunking fake news articles.

3.1.4 MODELLING

To develop a model that can accurately detect fake news, two different approaches were utilized in this project. One approach involved the use of traditional machine learning techniques, while the other approach utilized deep learning methods.

- **MACHINE LEARNING APPROACH**

To train and test the different models, the 'clean-text' column was vectorized using both CountVectorizer and TfidfVectorizer, which are vectorization techniques used to convert text data into numerical data suitable for machine learning algorithms. The data was then split into training and testing sets using the train_test_split function from the Scikit-learn library. The target variable, which was the 'label' column in the dataset, was encoded using the LabelEncoder object.

Feature selection was then applied using SelectKBest from the Scikit-learn library with the score_func= f_classif to select the best 7 features for the model. This was applied only to the Tf-id Vectorizer since the CountVectorizer could not apply feature selection.

Various classification algorithms such as Logistic Regression, Random Forest, Naive Bayes, Gradient Boosting Classifier, Decision Tree Classifier, and Extreme Gradient Boosting were used to train and test the model. A function, fit_and_score, was created to fit each model and calculate its accuracy score.

Overall, this approach effectively identified fake news using the selected classification algorithms. However, the performance of each algorithm varied, with some algorithms performing better than others. Further improvements could be made to the model by using more advanced feature selection techniques or experimenting with different hyperparameters for the selected algorithms.

- **DEEP LEARNING APPROACH**

The Keras library was used to build a sequential model for detecting fake news. The Tokenizer function was used to tokenize the words in the ‘clean-text’ column, and sequences of tokenized words were created. The sequences were then padded to ensure that they were of the same length using the pad_sequences function. A sequential model was created with an embedding layer followed by a bi-directional LSTM layer, and then two dense layers. The ‘Adam’ optimizer and binary cross-entropy loss function were used to compile the model. The model was trained on the training set and evaluated on the test set using the predict function. The predicted labels were obtained by rounding off the y_pred values to the nearest integer. The accuracy of the model was calculated using the accuracy_score function.

The deep learning approach showed promise in detecting fake news, achieving a high accuracy score. However, the model's performance may be affected by the quality and size of the dataset used for training. Therefore, further experimentation and testing may be required to improve the performance of the model.

3.1.5 MODEL EVALUATION

Several performance metrics were used to evaluate the effectiveness of the models. These metrics included accuracy, precision, recall, and F1-score. Accuracy measured the number of correctly predicted instances out of the total number of instances, while precision measured the number of correctly predicted positive instances out of the total predicted positive instances. Recall measured the number of correctly predicted positive instances out of the total actual positive instances. The F1-Score was the harmonic mean of precision and recall, giving equal weight to both metrics. These metrics were used to evaluate the performance of the selected models on both the train and test sets.

3.2 VERSION CONTROL MANAGEMENT

To ensure accessibility and organization of the personal project, version control management was implemented using GitHub. The source code of the project is available on the GitHub code repository, which can be accessed via the following link: JammalAdeyemi/FakeNews_detection: COS7045-B 001 Coursework - Advance Machine Learning (github.com)

CHAPTER FOUR

RESULTS

The study examined the effectiveness of various algorithms both traditional ML and Deep Learning in detecting fake news. The Bidirectional LSTM model, incorporating an Embedding Layer, demonstrated the highest accuracy rate of 99%. These promising results suggest that the proposed approach effectively identifies fake news, other model accuracy can be found in Table 1.

Classifier	Accuracy
Logistic Regression	0.983
Random Forest	0.976
Naive Bayes	0.944
Gradient Boosting Classifier	0.985
Decision Tree Classifier	0.984
Extreme Gradient Boosting	0.988
Bidirectional LSTM	**0.990**

Table 1. Models Accuracy Results

It is important to note that accuracy, on its own, is not a comprehensive evaluation of model performance. Hence, supplementary data has been included to aid in interpreting the results. Table 2 presents the classification report for the Bidirectional LSTM model, which highlights the precision, recall, and F1-score values for each class.

	Precision	Recall	F1-score	support
Real	0.99	0.99	0.99	4946
Fake	0.99	0.98	0.99	4392
accuracy			0.99	9338
macro avg	0.99	0.99	0.99	9338
weighted avg	0.99	0.99	0.99	9338

Table 2. Classification reports of Bidirectional LSTM

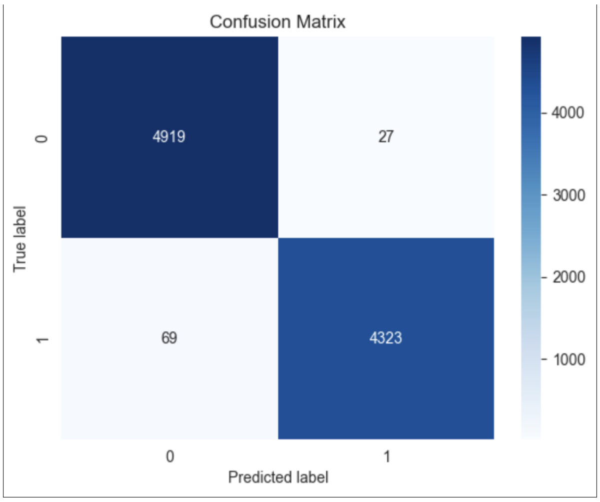

Fig 4.1 Confusion Matrix Results for Bidirectional LSTM

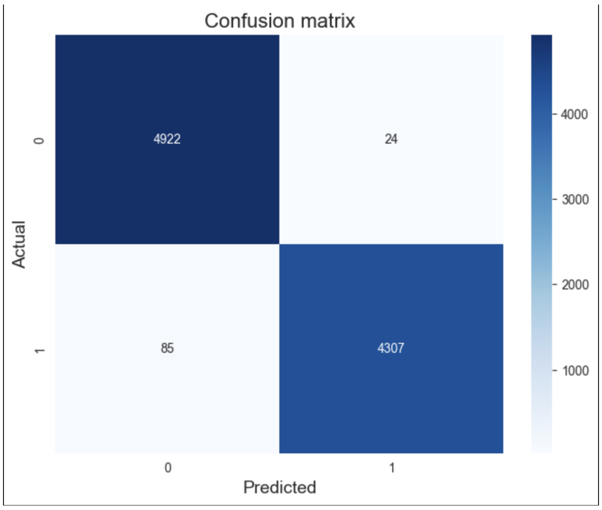

Fig 4.2 Confusion Matrix Results for Extreme Gradient boost

Additionally, Fig 4.1 & 4.2 illustrates the confusion matrix for the Bidirectional LSTM model & Extreme Gradient boost model, detailing the true positives, false positives, true negatives, and false negatives for each class. Fig 4.1, the Bidirectional LSTM model demonstrated a high level of accuracy by correctly classifying 4919 instances as true positives and 4323 instances as true negatives. However, it did make 27 false positive predictions and 69 false negative predictions, indicating that there is still room for improvement.

In contrast, Fig 4.2 shows that the XGBoost model also performed well, correctly classifying 4922 instances as true positives and 4307 instances as true negatives. However, it made 24 false positive predictions and 85 false negative predictions, indicating that it may not be as precise as the Bidirectional LSTM model.

Overall, both models showed promising results with high numbers of true positives and true negatives. However, when comparing false positives and false negatives, the Bidirectional LSTM model appears to have a slightly better performance than the XGBoost model. This suggests that the Bidirectional LSTM model may be a more suitable option for this particular classification task.

CHAPTER FIVE

CRITICAL REVIEW

The spread of fake news and disinformation on social media platforms has become a significant problem in recent years. Researchers are developing algorithms and techniques to detect and combat fake news effectively. The aim of this critical review was to develop and compare the performance metrics of two machine learning models that use text-based features to detect fake news. The best-performing model was found to be the Bidirectional LSTM. The choice of a bidirectional LSTM model for the detection of fake news is a significant one. Bidirectional LSTMs have proven to be effective in natural language processing tasks due to their ability to capture contextual information from both past and future sequences (Huang et al., 2017). This is particularly important in the context of fake news detection, as understanding the entire context of a sentence or text can help identify subtle linguistic cues or patterns that indicate misinformation. By incorporating bidirectional LSTM, the model can analyze the semantic meaning of the words and their relationships in both directions, enabling a more comprehensive understanding of the text and improving the accuracy of fake news detection. In comparing the results of this project with published academic sources, the findings are consistent with previous studies that have shown the effectiveness of machine learning and deep learning techniques in detecting fake news (Choudhary et al., 2023; Saxena et al., 2022). The use of Bidirectional LSTMs in this project is also consistent with previous studies that have demonstrated their effectiveness in natural language processing tasks.

5.1 FUTURE WORK

One of the primary limitations of the Bidirectional LSTM model is its reliance on text-based features. While the model is effective in identifying fake news in text-based formats, it may not be as effective in detecting fake news in other formats such as videos. As fake news often spreads through images and videos, this limitation could hinder the algorithm's overall effectiveness. To address this limitation, researchers could incorporate non-text-based features, such as images and videos, into the algorithm to improve its effectiveness.

Future work could address these limitations and improve the algorithm's effectiveness by incorporating non-text-based features, developing techniques to detect fake news that has yet to be encountered, and improving the algorithm's interpretability. Techniques such as bagging and boosting could be used to improve the performance and robustness of the algorithm.

GANs could be used to generate realistic images and improve the performance of image recognition models.

5.2 LEGAL, SOCIAL AND PROFESSIONAL ISSUES

The detection of online fake news using traditional methods and deep learning raises important legal, social, and professional issues. One relevant issue is the dataset's timeliness, as the study covers news from 2016-2018, which may not reflect current trends in fake news dissemination. Here are some other main concerns:

1. Legal issues: One legal issue related to detecting online fake news is the protection of freedom of speech. There is a delicate balance between combating fake news and ensuring that individuals' rights to express their opinions are not violated. Additionally, false positives can lead to accusations of defamation or harm to the reputation of individuals or organizations. Hence, algorithms used to detect fake news must have a low false positive rate and high accuracy.
2. Social issues: Online fake news has the potential to harm social relationships by spreading misleading information and creating distrust. It can also be used to manipulate public opinion, particularly in political contexts. Detecting fake news can help mitigate these negative effects, but there is a risk that it may also lead to censorship or the restriction of certain types of content. It is crucial to consider how the detection of fake news may impact social dynamics and ensure that any measures taken do not violate individuals' rights.
3. Professional issues: Detecting online fake news is a complex task that requires expertise in various fields, such as data science, journalism, and law. It is essential to ensure that any individuals or organizations involved in detecting fake news have the necessary qualifications and adhere to professional standards. Conflicts of interest or biases need to be addressed, especially in cases where the detection of fake news involves political or financial interests. Therefore, transparency and impartiality are critical in detecting fake news.

In conclusion, detecting online fake news requires careful consideration of legal, social, ethical, and professional issues. Although it is crucial to combat fake news, measures taken must not violate individuals' rights, restrict content, or cause harm. Professionals involved in detecting fake news must adhere to professional standards, avoid conflicts of interest, and maintain transparency and impartiality.

CHAPTER SIX
CONCLUSION

After careful analysis, it can be concluded that the primary objective of the project which was to create a dependable and precise ML model for the automatic classification of news articles as legitimate or fraudulent was achieved. The objectives of the project were achieved by assembling and processing labelled news datasets, utilizing natural language processing techniques to prepare the textual data, implementing traditional machine learning algorithms, and creating a Bidirectional Long Short-Term Memory (LSTM) model. The results of the experiments demonstrate that the Bidirectional LSTM model surpasses traditional machine learning models in identifying fake news. Nonetheless, the Bidirectional LSTM model's drawback is its reliance on text-based features, which may limit its effectiveness in recognizing fraudulent news in other formats, such as videos.

The key contribution of this project is the verification that machine learning can be utilized distinctively to address the issue of classifying false news. The Bidirectional LSTM model can identify a wide array of sophisticated linguistic patterns that may be difficult for humans to discern. This model can assist humans in identifying fraudulent news by detecting patterns of words such as "vague," "indecisive," "allusive," and "proof" to recognize authentic news. Future research can improve the algorithm's effectiveness by incorporating non-text-based features, developing techniques to identify fake news that has yet to be encountered, and enhancing the algorithm's interpretability.

In summary, this project has demonstrated the potential of machine learning and deep learning techniques in detecting fraudulent news, providing a foundation for further research to increase the accuracy and efficacy of automatic fake news detection.

REFERENCES

Bhardwaj P, Yadav K, Alsharif H and Aboalela R. (2023). GAN-Based Unsupervised Learning Approach to Generate and Detect Fake News. International Conference on Cyber Security, Privacy and Networking (ICSPN 2022). 10.1007/978-3-031-22018-0_37. (384-396).

Chattopadhyay A, Beyene N and Rana S. (2023). Analyzing Multimodal Datasets for Detecting Online COVID Misinformation: A Preliminary Survey Study 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC). 10.1109/CCWC57344.2023.10099147. 979-8-3503-3286-5. (0147-0153).

Choudhary A and Arora A. (2023). Comparative Analysis of Transfer Learning and Attention-driven Memory-based Learning for COVID-19 Fake News Detection. International Conference on Innovative Computing and Communications. 10.1007/978-981-19-2821-5_3. (29-39).

Gupta A, Anjum A, Gupta S and Katarya R. (2022). Recent Trends of Fake News Detection: A Review. Machine Learning, Advances in Computing, Renewable Energy and Communication. 10.1007/978-981-16-2354-7_43. (483-492).

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

Kaul A and Guaba R. (2022). Communication through Social Media: Fake or Reality. Communication Management. 10.5772/intechopen.99719.

Kiran A, Shetty M, Shukla S, Kerenalli V and Das B. (2023). Getting Around the Semantics Challenge in Hateful Memes. Computational Intelligence and Data Analytics. 10.1007/978-981-19-3391-2_26. (341-351).

Lahby M, Aqil S, Yafooz W and Abakarim Y. (2022). Online Fake News Detection Using Machine Learning Techniques: A Systematic Mapping Study. Combating Fake News with Computational Intelligence Techniques. 10.1007/978-3-030-90087-8_1. (3-37).

Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2117-2125).

Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767.

Saxena A, Saxena P and Reddy H. (2022). Fake News Detection Techniques for Social Media. Principles of Social Networking. 10.1007/978-981-16-3398-0_15. (325-354).

Vosoughi, Soroush, et al. “The Spread of True and False News Online.” Science, vol. 359, no. 6380, 9 Mar. 2018, pp. 1146–1151, www.science.org/doi/full/10.1126/science.aap9559, https://doi.org/10.1126/science.aap9559.

Wei Z, Pan H, Qiao L, Niu X, Dong P and Li D. (2022). Cross-Modal Knowledge Distillation in Multi-Modal Fake News Detection ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 10.1109/ICASSP43922.2022.9747280. 978-1-6654-0540-9. (4733-4737).

Xu F, Sheng V and Wang M. (2021). A Unified Perspective for Disinformation Detection and Truth Discovery in Social Sensing: A Survey. ACM Computing Surveys. 55:1. (1-33). Online publication date: 31-Jan-2023.