DETECTION OF FAKE NEWS USING NATURAL LANGUAGE PROCESSING AND STATISTICAL TECHNIQUES

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Candidate of **Master of Science in Software Engineering (MSSE)** at the National University of Modern Languages do hereby declare that the thesis **Detection of Fake News using Natural Language Processing and Statistical Techniques** submitted by me in partial fulfillment of MSSE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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ABSTRACT

Detection of Fake News using Natural Language Processing and Statistical Techniques

The rapid growth of fake news in online media and social platforms has become a major concern in recent years. To address this problem, we propose a system that integrates Statistical techniques, Machine Learning (ML), and Natural Language Processing (NLP) methods to identify fake news. We extract features using the Term Frequency- Inverse Document Frequency (TF-IDF) method and evaluate the classifier's performance using metrics such as accuracy and precision. We have used three different ML algorithms for classification, namely Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR). Our results show that LR with Maximum Likelihood Estimation (MLE) outperforms other classifiers, achieving an accuracy of 95%. Our study includes the use of NLP methods for feature extraction, which improves the accuracy of fake news detection. In addition, we demonstrate that LR with MLE is an effective approach for identifying fake news by reducing the complexity and dimension of features, which can help to prevent the spread of fake news. The study provides a valuable contribution to the field of fake news detection and highlights the importance of integrating NLP methods with Statistical and ML techniques to improve the effectiveness of fake news detection.

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LIST OF ABBREVIATIONS

NLP	Natural Language Processing
ML	Machine Learning
AI	Artificial Intelligence
NB	Naive Bayes
DT	Decision Tree
SVM	Support Vector Machine
LR	Logistic Regression
MLE	Maximum Likelihood Estimation
FN	Fake News
TF	Term Frequency
IDF	Inverse Document Frequency
SMF	Social Media Platforms
BOW	Bag of Words

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I owe my profound thanks and cordial sense of gratitude to Almighty ALLAH, the Most Beneficent and Merciful, Who blessed me with courage, potential, and capability to complete my MS work.

I profusely thankful to my parents who brought me to this stage of life, and their guidance which is an encouragement for me in every step of my life.

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DEDICATION

Dedicated to my Parents, Teachers, and Friends

CHAPTER 1

INTRODUCTION

1.1 Overview

The popularity of fake news has been rising quickly. Although it is not a recent problem, it has just gained considerably more attention. It has been noticed that humans tend to believe false information, which makes spreading false information smoother. Fake news is one of the biggest dangers to the idea of reasonable truth due to its capacity for propagation, acceptance, and destruction [1]. It has a significant ability for destroying the economy, justice, media, and eve democracy [2-5]. However, social media is becoming a new source of information in the current age of the internet. Online media has gotten progressively well-known for news consumption in the previous decade because of its simple access, quick scattering, and least expense. The primary cause of the development of false news is as it is being produced and distributed online more rapidly and affordably than through conventional media channels such as television or newspapers. Common people who mistakenly spread incorrect information without knowing it might be the source of fake news [6]. In any case, web-based media additionally empowers the spreading of fake news, i.e., with intentionally incorrect information. Fake news via web-based media can have critical negative social impacts. So, the detection of fake news via web-based platforms has become a research domain in the past few years that is getting huge attention among researchers. The phrase fake news initially referred to misleading information that was frequently misreported and spread as important news. However, the meaning of this word has changed with time, and it is now associated with the spreading of incorrect material on online platforms [7]. The news material may be fully false, created specifically to mislead the viewer, or this may be deceptive material that uses false information to address a certain topic. On social media, false information is constantly shared and believed because people struggle to distinguish fake news from real news [2-5].

A person finds it challenging to distinguish between true and incorrect information while being overloaded with deceptive information that is repeatedly received. People also likely to believe fake news because traditional communication channels are currently being viewed with doubt by the general population.

There were 71.70 million social media users in Pakistan in January 2022. The number of social media users in Pakistan at the start of 2022 was equivalent to 31.5 percent of the total population. There were 4.74 billion social media users around the world in January 2022, equating to 59.3 percent of the total global population [8].

The use of social media has increased significantly during the past ten years. Nowadays, a lot of information is uploaded on social media sites like Facebook and twitter, which were introduced in 2004 and 2006, respectfully. These platforms have made it simpler than ever to spread false information to a large audience using a variety of strategies [9]. In some cases, social media can propagate information more quickly than traditional media such as newspapers and television [10]. It can cover news that other media will be unable to report; this kind of fake news is developed to support a specific plan [11]. The usage of social media as a news collecting technique has grown in recent years. In 2012, just 49% of people said they got their news from social media, but now nearly 70% of the population uses it [12]. Today, anyone can upload anything on the internet whether it is true or not. People can be misled as a result of this, either willingly or mistakenly, and didn’t supposed to think before sharing such news with the global world. A serious misinformation outbreak, which had a global impact, was seen in American culture in 2016, during the US presidential elections. Election results in Brazil in 2018 experienced a similar outcome. The 2018 Brazilian elections experienced a similar outcome.

1.2 Impact and Disadvantages

Fake news has rapidly become a social issue, being spread to influence person's attitudes by spreading incorrect or unconfirmed information. It is a key tool in information warfare, which is one of the emerging cyber security threats. But sometimes it becomes difficult to decide which one is fake, and which one is authentic. After the US 2016 election, the phrase fake news became widely used. Here are some facts about fake news in the US where 62% of people use social media to acquire their news.

Some people believed that Donald Trump would not have been elected as President if misleading information hadn't been used against his opponents [13]. Fake news is a significant issue that can easily mislead individuals and create confusion within a community, whether it be in social, political, or economic contexts. In the business world, fake news can have severe consequences as it can negatively affect a company's stocks and lead to significant financial losses. Promoting incorrect information has even become a business in recent years, with many documented examples [14]. It is shocking to note that Facebook users share fake news more frequently than genuine news [4].

However, the impact of fake news is not restricted to politics; it affects other areas such as health, science, and sports as well. The financial markets are also a key area where fake news can have an impact, as it can influence how individuals respond to and engage with real information [15].

To combat the spread of misleading news, it is important to create a system that can swiftly recognize and reduce its impact on social media. Additionally, during election campaigns, fake news is often used as a weapon to defame political opponents, significantly impacting the outcome of elections. Therefore, educating individuals about the harmful effects of fake news is crucial [16].

1.3 Fake News Characterization

Basically, there are two types of fake news,

1. ***Misinformation***
2. ***Disinformation***

1.3.1 Misinformation

The purpose of the person or platform sharing the information distinguishes it from misinformation. Misinformation is delegated "fake or deluding content including lies, conspiracy theories, bogus reports, and misleading content features." Misinformation isn't purposely planned to beguile. All things considered, it means to shape or change popular assessment on a particular given point.

1.3.2 Disinformation

Disinformation can be spread utilizing a large number of similar strategies as misinformation, misleading content, and made-up reports. Disinformation is made to trick people. Author's [17] reports found that 24.8% of readers shared a piece of news they either knew was false when they saw it or thought it was made-up news. There are a variety of reasons why individuals' online media identities or even professional accounts could disseminate false information. It's possible that they're doing it to increase their use of social media, attract more customers to their brand or page, elicit an emotional response, or divert attention. Online media can be problematic because, as was already mentioned, the length of readers' attention and the amount of content their spans might make it possible for disinformation to spread unchecked.

1.4 Challenges

Challenges: During my working on fake news detection, I have faced several challenges during the preprocessing stage. Some of the key challenges include dealing with ambiguity in the language used in fake news, ensuring the quality of the data, handling domain-specific language, addressing source bias, processing large volumes of data, and selecting the appropriate preprocessing techniques. These challenges have required me to develop a deep understanding of the data and use a combination of techniques to effectively preprocess the data for use in models for fake news detection. I have also faced difficulties in processing large volumes of data and selecting appropriate preprocessing techniques. To overcome these challenges, I was kept up-to-date with the latest techniques in NLP and statistical analysis to improve the accuracy of fake news detection models. Recently, multiple models have used to achieve an accuracy between 60-75 percent, including the Naive Bayes classifier, Logistic regression [18]. Deep Learning systems will also be more effective at detecting fake news but with large dataset [19]. In the study, we detect fake news by using NLP, ML, and statistical techniques.

1.5 Traditional Solution

Another way to detect fake news disseminated on digital platforms is the direct Fact-checking, typically performed by expert journalists, involves assessing the truthfulness of news stories or claims by comparing them with reliable sources [20]. Organizations such as "Snopes.com," "PolitiFact," "FactCheck.org”, in Brazil serve as examples. However, traditional fact-checking is time-consuming as it requires a detailed analysis to support the verdict. With the exponential growth of online information, traditional fact-checking methods struggle to keep up [21]. To address this challenge, computational fact-checking studies, including automatic detection of fake news, are emerging."

Currently, there are mainly two approaches to perform automatically fake news detection [22]. First, (i) there are efforts that propose solutions based on artificial intelligence techniques such as supervised, weakly supervised via reinforcement, active and deep learning, and also, based on specific strategies such as block chain technology [23]. Second, (ii) other efforts to perform automatically fake news detection comprise works which aim at exploring tools or online systems for monitoring online misinformation [24]. These systems were proposed and used as countermeasures to the fake news problem on different digital platforms.

As a result traditional fact-checking methods face challenges in today's information landscape. The volume and speed of online information overwhelm fact-checkers, making it difficult to keep up. Additionally, limited resources also pose a challenge, as fact-checkers may not have the capacity to thoroughly analyze all the information being circulated. Complementary approaches like computational fact-checking and automated detection systems are needed to effectively combat the spread of misinformation.

1.6 Fake News Spreading Process

In order to spread, control, and consume fake news on social networks, a number of entities, people, and organization engage. The difficulty in detecting and reducing the spread of false news is made much further difficult by the diversity of parties engaged. Due to social media's vast scale, wide audience, and capability for collaborative content sharing, the spread of fake news significantly depends on it to the harm of traditional media. Because of growing accessibility and acceptance of Internet access and computer-mediated communication social media websites have emerged as the most common platform for the propagation of fake news [25]. The detection of fake data can be done manually by qualified journalists.

Although this method is the most popular, it is incompatible with the capacity of content being produced and shared on web based media at the moment. Automated approaches that verify the accuracy of news that is disseminated via the Internet typically combine ML methods and NLP, to address this issue.

1.7 Methods to Convert Words into Vectors

1.7.1. Bag of Words (BoW)

The text content is transformed into numerical feature vectors using this vectorization technique. By mapping all the words in the corpus to a vector for the machine learning model, Bag of Words takes a document from a corpus and turns it into a numeric vector.

Figure 1: Bag of Words

Bags-of-words is a straightforward representation in which the input text is changed into a bunch of words known as a bag shown in Figure 1. Information concerning multiplicity is stored in multiset. It keeps track of words that how many of times they appear in a sequence as tuples. It keeps track of words and the number of times they appear in a sequence as tuples. It is used as a plain vector because it has a map storing which word matches which index. The count vectorizer from the Sklearn library can be used to encode a document using the Bags of Words method. We carried out two operations in our text vectorization method.

1.7.2. Vector Creation

Here, the number of distinct words in the document was equal to the vector size for a specific document. We filled each entry of a vector for each document with the matching word frequency for that specific document.

Let's use the following example to get a clear understanding:

For Example: importing "from sklearn.feature extraction.text. This document is the first document. This document is the second document. This document is the third document. Is this the first document?

CountVectorizer () = vectorizer X equals vectorizer. Fit transform (corpus)

Print (vectorizer.get feature names ())

['and,' 'document,' 'first,' 'is,' 'one,' 'second,' 'the,' 'third,' and 'this'] print(X.toarray())

[0 1 1 1 0 0 1 0 1]
[0 2 0 1 0 1 1 0 1]
[1 0 0 1 1 0 1 1 1]
[0 1 1 1 0 0 1 0 1]

In the above example, there are nine words in the vocabulary. The matrix thus contains nine columns. Let's interpret [0 2 0 1 0 1 1 0 1] in the second line. As can be observed, there are no occurrences of the first element, which refers to the first vocabulary index, the word 'and,' in the line 'This document is the second document.' The second example shows that the word "document" was used twice. We can understand each component of the matrix in the same way.

1.7.3. N-Gram

The N-gram method is frequently applied in statistics (NLP). Character sequences are modeled differently for various language identifications. N-grams of texts are frequently used in natural language processing and text mining tasks.

For instance, 'The cow jumped over the moon is an example'. The n grams, in this case, is N=2 (also known as bigrams) might be:

- The cow
- cow jumped
- Jumped over
- Over the
- The Moon

So in this situation, there are 5 n-grams. Being mindful of the fact that we transitioned from the->cow to cow->jumps to jumps->over, etc., to create the next bigram, we are effectively shifting one word forward.

1.8 Classifier

Machine learning refers to the development of algorithms and statistical models that can learn from data without being explicitly programmed, and that can use this learned knowledge to make predictions or take actions. The objective of machine learning is to enable computers to automatically identify patterns and relationships in data.

ML algorithms can be classified into supervised and unsupervised forms. While supervised learning algorithms have input data and desired output data provided for them through labelling, unsupervised algorithms deal with data that is neither classed nor labelled. An unsupervised algorithm, for instance, might categories unsorted data based on similarity and dissimilarity.

Machine learning is the field of computer science that involves, adaptive programs that can learn from training data are developed. Machine learning can take many different forms, including reinforcement learning, semi-supervised learning, supervised learning and unsupervised learning. Normally, preparing data for two sets training data and test data, the first step is creating a machine learning model. Knowledge gains by Machine learning from practice data. Using test data, the users measure the trained machine learning model. In order to ensure that we can confidently predict future unknown data using the trained model, the test data evaluation is performed. Users select a machine learning model for the right task because dissimilar methods are suitable for various tasks. In this study, we focus on supervised learning, which includes SVM, LR and NB.

1.8.1. Supervised Learning

The machine learns while being supervised in supervised learning. It has a model that can make predictions using data that has been labeled. A dataset that has been labelled indicates that you already know the expected output.

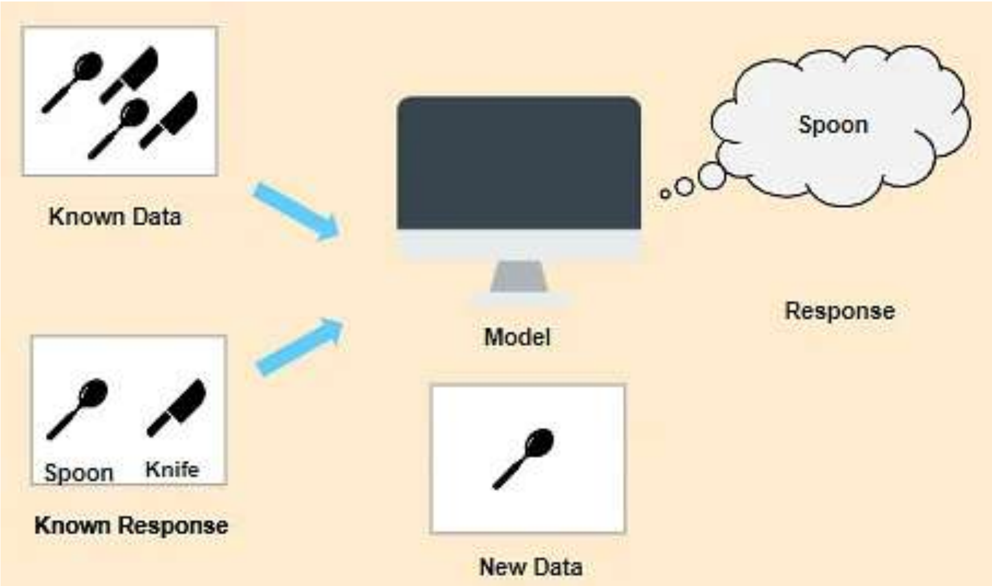

Figure 1.2: Supervised Learning

In this example, we have Figure 2 of a 'spoon' or 'knife'. The machine receives this known data and processes it to assess and learn the correlation of the images based on their features, such as shape, sharpness, size, etc. Now, using the historical data, the machine can properly predict that a fresh image fed to it without a label is of a spoon.

Following are the two categories of supervised learning:

1. Classification

2. Regression

1. Classification

When an output variable has two or more distinct classes, classification is performed. For instance, true or untrue, male or female, yes or no, etc.

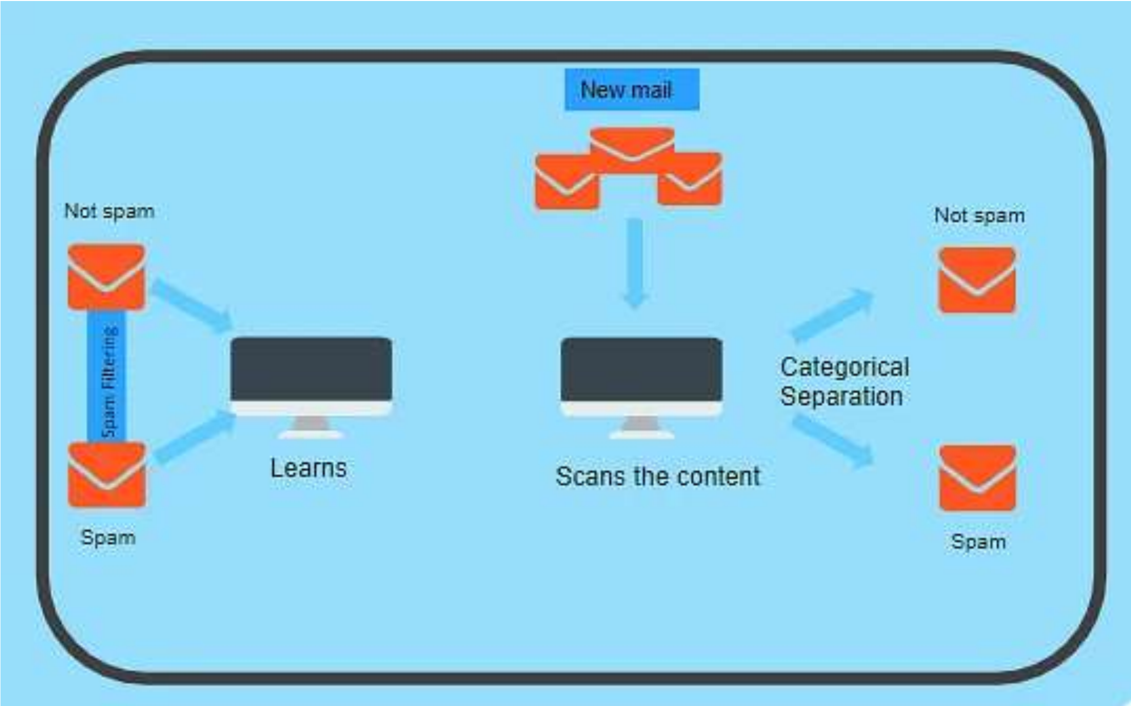

Figure 1.3: Classification

In the figure 3 we explain the whole process. First we must teach the computer what a spam email looks like in order to predict if a message is a spam or not. This is done using a variety of spam filters, which examine the email's header and body before looking for any misleading information. The use of specific keywords and blacklist filters by spammers who have already been banned.

The algorithm chooses whether fresh incoming mail should go to the inbox or spam bin based on the content, label, and spam score.

2 Regression

When the output variable has a real or continuous value, regression is utilized. A modification in one variable is related to a change in the other in this situation because there is a relationship between the two or more variables. For instance, pay based on job history or weight dependent on height, etc.

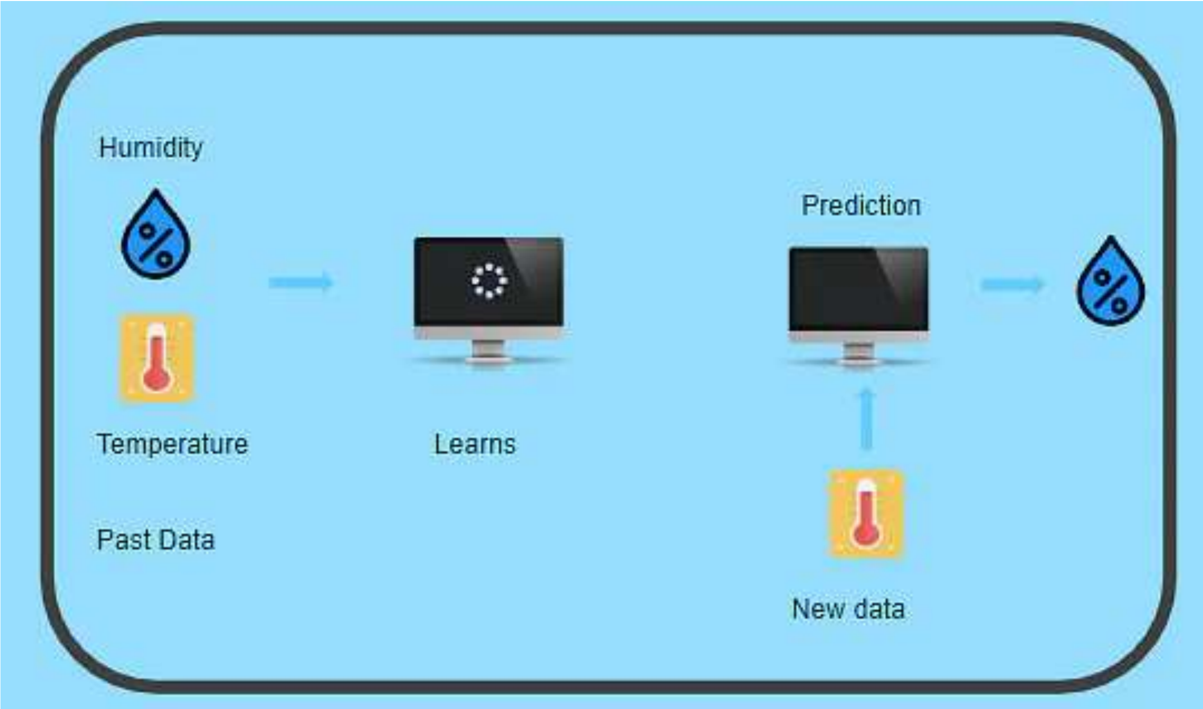

Figure 1.4: Regression

Let's think about the two variables temperature and humidity as shown in the figure 4. Humidity is the dependent variable and temperature is the independent variable in this situation. The humidity falls as the temperature rises.

The model is fed these two variables, and as a result, the machine discovers their relationship. Once trained, the method can accurately forecast the humidity grounded on the temperature.

1.8.2 Unsupervised Learning

Unsupervised learning, as the name suggests, uses machine learning methods without using training datasets to supervise models. Instead, models employ the available data to highlight hidden patterns and insights. It is also defined as, machine learning techniques known as ‘unsupervised learning’ which allow models to be trained on unlabeled data and then allowed to operate unsupervised.

Unsupervised learning can be divided into the following categories:

1. ***Clustering***
2. ***Association***

1. Clustering

A technique for organizing objects into clusters so that the objects that share the most similarities share little to none and stay in one group with the objects in alternative group. The similarities between the data objects are discovered by cluster analysis, and they are then categorized according to whether they exist.

2. Association

A rule-based machine learning technique used to figure out the probability that items in a collection will appear together.

1.9 Problem Statement

Fake news is a significant problem globally, leading to widespread misinformation and social polarization. The presence of a large number of features in textual data poses challenges for achieving high accuracy in analysis and classification tasks. Deep learning methods, while effective, often come with high computational complexity [26]. To address this, there is a need to explore statistical techniques that can reduce the dimension of the features to improve the accuracy by combining natural language processing (NLP), statistical methods, and machine learning algorithms, while minimizing complexity in textual data analysis [27].

1.10 Research Questions

RQ1: What are the techniques to identify the significant features in the detection of fake news?

RQ2: How to develop a system for accurate detection of fake news?

1.11 Objectives

OBJ1: To identify the significant features in the detection of fake news.

OBJ2: To develop a system for accurate detection of fake news.

1.12 Scope of Study

Fake news classification and detection by using Machine Learning approaches have been performed but still to improve the result for detecting fake news. NLP methods have been used to extract features [3]. ML methods and Statistical techniques have been used to find out the best features for prediction and to develop even more accurate ensemble models.

1.13 Summary

This chapter establishes a comprehensive framework for detecting fake news. It starts by highlighting the significant impact and drawbacks of fake news. It then differentiates between misinformation and disinformation. The challenges in addressing fake news are explored, considering its evolving dissemination strategies. Traditional solutions' limitations are discussed, underscoring their inadequacy in the dynamic digital landscape. The process of fake news dissemination and its impact on public perception are analyzed. Methods to transform textual content into numerical data, like Bag of Words and N-Gram techniques, are introduced. Classification, crucial for fake news detection, is explained, encompassing supervised and unsupervised learning. The chapter concludes by defining the research problem, stating research questions, objectives, and scope. In essence, it lays a robust foundation for addressing the complexities of fake news detection in the digital era.

The rest of thesis is organized as follows:

Chapter 2: Background

In this chapter, a comprehensive background of the subject matter will be provided. This includes an exploration of the fundamental concepts and key principles that underpin the research.

Chapter 3: Literature Review

Delving into existing research, Chapter 3 will offer a comprehensive review of the current literature related to the topic. This review will highlight relevant theories, studies, and findings that contribute to the context of the research.

Chapter 4: Methodology

In Chapter 4, the research methodology adopted for this study will be thoroughly elucidated. This chapter will explain the chosen research approach, data collection techniques, tools, and analytical methods employed to address the research questions or objectives.

Chapter 5: Experimental Results

The empirical outcomes of the research will be presented in Chapter 5. This section will comprehensively detail the results obtained from the experimentation or investigation, providing clear insights, data analysis, and findings derived from the research process.

Chapter 6: Conclusion

Chapter 6 marks the culmination of the thesis. Here, the entire research journey will be summarized, and the key takeaways drawn from the study will be discussed. The conclusion will reflect upon the significance of the findings in relation to the initial research objectives, and potential avenues for further research may also be suggested.

By following this organized structure, the thesis aims to provide a cohesive and insightful exploration of the subject matter, guiding the reader through a logical progression of information and analysis.

CHAPTER 2

LITERATURE REVIEW

2.1 Fake News

Fake news is an old concept. The news posted on social media that is unconfirmed and misleading is known as fake news. Fake news, according to the author [28], is defined in terms of the reliability of the material, the author's motivation, and if the information is presented in the form of news. Fake news, according to a recent study, is defined as verifiably false or purposely false information which misleads the reader [12]. Multiple events and problems are caused by fake news. The term during the US 2016 elections, fake news has become popular as a result of incorrect information [29]. According to the New York Times, fake news refers to propaganda or deceptive content that spreads false information on social media [30]. The term word of the year for fake news has been used because of the extremely difficult circumstances that occurred in Australia in 2016 [31].

2.2 News Media Ecosystem in Digital Platforms

Scholars in several fields, including political science, journalism, and communication, have long studied the news media. However, it has been an interesting topic to computer researchers as a result of news media's use of the Web and digital platforms. News media have been publishing in digital form as the digital era has come into being. As a result, computer scientists have looked into issues relating the news system on social media platforms, which typically has various objectives in mind due to the abundance of news information available digitally, given this complicated situation, the possibility for new applications as well as the creation of new difficulties.

Production, consumption, and dissemination are the three key parts that make up the foundation of the news ecosystem on digital platforms. Before the digital platforms, news stories were authored only by traditional news media organizations for example newspapers or journalists who are independent. As digital platforms have grown, one important aspect of news production in these settings is that anyone can do it. For example, anyone can create a user on a digital platform to publish and distribute news for free. The way that news has also evolved over time as per consumption, evolving from old printing media to digital media like; radio and television to, more recently, internet news and digital platforms, where news is frequently more timely and less expensive to receive than in traditional news media. For instance, according to a Pew Research Center survey, 62 percent of US citizens are news consumers mostly through social media platforms [32]. This proportion in Brazil exceeds 66 percent, according to a study by the Institute of Reuters [04]. Last but not least, digital platforms introduce new methods for communication and involvement, enabling people to share and public news items as they see fit.

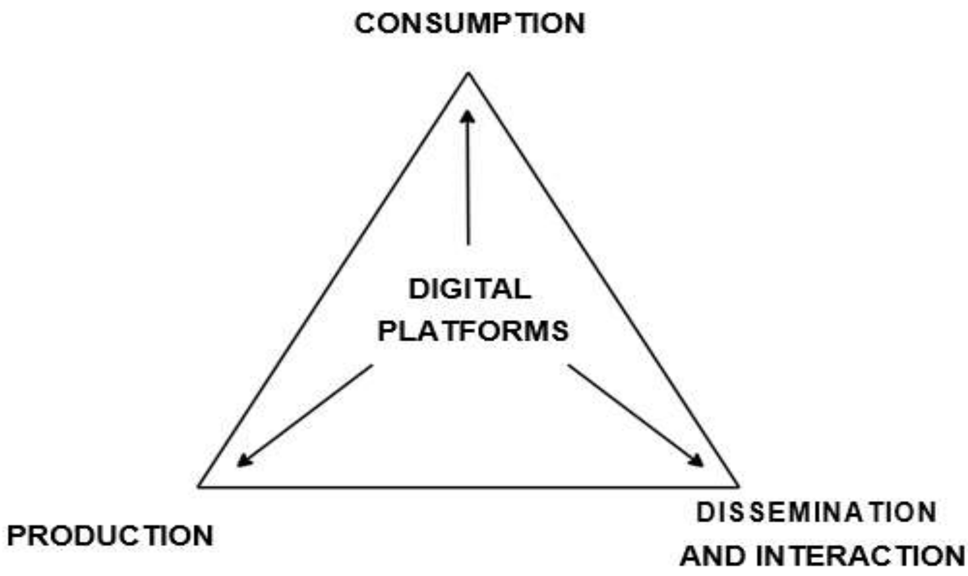

Figure 2.1: News Ecology

Different Computer Science initiatives are being made in response to the introduction of digital platforms into the news ecosystem in an effort to improve comprehend these variations and offer solutions to support this phenomenon at several phases. These initiatives are divided into three sets which can be seen in figure 5 which are interconnected that correspond to the key elements of the news ecosystem on digital platforms.

2.2.1 Production

We begin by going over earlier research that looked at the nature of creating online news and how the introduction of digital platforms has changed this process. Patterns and coverage of news content. Studies [33] focus on many aspects, including photos, pictures, videos of several news, as they study the patterns of news material. There are methods for calculating the effect of news material on the platforms of digital social media.

Natural language processing methods are combined and accomplished of generating signs of the social platform's influence of the provided content by comparing their relevance to an arbitrary news article [34]. Specific aspects of contents of news are specified by some studies, such as how quickly bad news spreads on Twitter compared to positive news, can have an impact on the dynamics of digital platforms . Therefore, to comprehend how attributes collected from news items are related to local large-scale datasets of online news are also utilized coverage of the world news, focusing on various elements, for example disaster, epidemics, as well as pandemics [35]. However, news is covered on digital platforms frequently depends on how it is given a shape and that is dependent on that , mostly by the main media [36]. There still some discrepancies exist between what the general people creates on social media platforms and what online news outlets print.

To identify news and the occurrences from web sources. Digital platform services are widely employed as news sources and to disseminate information about current events. The automated detection of events based on activity on digital platforms is thus the subject of a significant amount of news-related research by computer scientists. These initiatives include filtering through the complexity of information on digital platforms to find and confirm the accuracy of breaking news and trendy issues [37, 38].

Overall, these technological advancements as well as along the availability of sources of information on digital platforms have provided various opportunities which are reshaping way by which journalism is practiced in the society of ours [39]. Using social media platforms as a method of supporting journalists the relationship between journalists and their work has evolved as a result of the use of digital platforms in production of news [40]. Around 500 journalists from 15 different countries were interviewed for the fourth annual Digital Journalism Study in 2011, which discovered that nearly 50 percent of which used social media as their main source of information of news. Social media is being utilized more and more by journalists to find such relate, enhance writings of them, finally, they have created share news [41]. It is not that surprising, current research efforts are focused on recommending technical solutions that can aid and support these journalists in these scenarios [42].

The digital age has presented a challenge in terms of determining the credibility of news. This is because journalists, fact-checkers, and readers alike are finding it difficult to discern trustworthy information from a wider range of unreliable sources on digital platforms. Additionally, a growing number of news events are initially being reported on digital platforms before being covered by traditional news outlets. Recently, digital platforms like Twitter, Facebook, and WhatsApp have gained widespread popularity, and have become a significant medium for spreading false information. To address this problem, there are two types of solutions, one is to research and understand the phenomenon more through such studies for example. It is revealed by the studies that false information spreads faster as compared to accurate news on digital platforms, highlighting the difficulty of the problem in this digital life. To tackle this problem, another approach is to develop methods for assessing the truthfulness of news, including exploring fact-checking as a method to control the spread of disinformation on digital media [43-45]. This topic will be more debated in future sections.

To increase participation, it is significant for news websites to have strategies in place to grab the attention of readers and entice them to click through to the article. This can be achieved by using compelling language, graphical elements for example photographs, color, layout, and front page design, click bait headlines [46]. It is essential for news sites to implement these methods because online readers frequently only have a limited amount of time to consume news. Previous research has proposed a simple way to measure how much clicks individual words get and how the timing of the news and the words used in the articles affect the click-through rate of the news. This research shows that finding the right words to use in headlines can be beneficial in increasing the number of clicks on articles of news in near the future [47].

Unfairness in news is a prevalent concern for readers of digital platforms, as they may not always be aware of the bias of the news outlets they are consuming [48]. To measure the bias of a news organization, traditional media has used two main strategies: (i) one approach is to directly measure bias by analyzing the content published by the news outlet, specifically the coverage of significant events [49].

In the second strategy to measure the bias of a news outlet is to analyze the readership, which suggests that the content and views of the news source will influence the biases of its audience. In recent times, there have been efforts to create scalable methods to automatically and accurately determine the bias of many news sources on social media such as Twitter and Facebook. Additionally, there are efforts to understand how these biases can be presented and conveyed to the readers [50].

2.2.3 Consumption

The advent of social media platforms as a new tactic of producing, distributing, and consuming news allows users to access material directly. As a result, some emerging studies are focusing on investigating different aspects of consuming news on social media platforms, including patterns of reading, methods for the enhancement of consumption, and techniques to encourage reading, such as news recommendations and visualization. Research has extensively examined reading patterns on online portals of news [51], including analyzing differences based on gender and age, and the role of geographic information in news consumption. However, consuming news on digital platforms is different, as there is a vast number of news articles available, and news providers are under pressure to find ways to capture the attention of readers, which in turn affects the production of news. Consequently, some studies are trying to identify the reading patterns of online news readers, focusing on the freedom of choice offered by platforms of digital as well as exploring how these patterns may be utilized to improve the design of news recommendation systems and evaluate the text quality [52]. Furthermore, there are studies that investigate the consumption of news on mobile devices. The advent of mobile devices has transformed the way information is accessed, making it more convenient to consume news from anywhere and at a low cost. This has significantly impacted the news ecosystem, particularly in terms of consumption. The use of mobile devices to access news has become a regular part of readers' daily lives [53]. As a result, some studies are emerging in order understand the consumption of online news through smartphones [54] and for the proposition of new mobile apps in order support this consumption. Such apps can record users' interactions with news unobtrusively and detect patterns in their reading behavior, which enables personalization and improves their experience. Recommendation news for readers can be an effective way for encouraging them to consume more. There are various approaches that aim to identify what users are typically interested in reading, such as by analyzing their previous behavior or past clicks [55]. However, there are few strategies that explore diversifying recommendations [56] for avoiding to create bubbles of filter. It is demonstrated by the studies that personalization of news digests can improve the user experience and increase engagement during news reading. With the overwhelming amount of news which are being produced every day, it can be challenging searching for relevant news for users. To address this problem, various several have emerged for making searching for news more efficient, such as focusing on targeted subjects, features of contents, or using content generated from users. There is also new way for summarizing trending topics this is done by finding the most representative and related information from social media posts and news. In addition, it is very significant to help the users quickly understand and act on the huge amount of the data, and one of the best ways to do that is through the technique of visualization. As a result, some studies aimed for the proposition of such strategies for organizing and to display news stories in a hierarchical map which works as a tool in order to browse news online. This allows users for the navigation through the news based on topics or geographical locations, for example. Additionally, some efforts have showcased a real-time application that are based on that visually representations an ideological map of different media sources. Predicting which news stories will be read by readers is becoming more and more popular. Studies have examined the connection between the popularity of the news and other features of the news, like the tone of the headlines. With a concentration on temporal characteristics, comments as a measure of popularity or dynamics of social, ranking approaches or regression and classification algorithms can be used to assess the popularity of news. Predicting the popularity of news pieces on digital platforms has become increasingly difficult as a result of context, network properties, and content [57].

2.2.3 Dissemination and Interaction

Studies have tried to find out how news is shared on digital platforms because they have grown to be an important avenue for news distribution. In this context, several researchers have carried out an exploratory investigation with an emphasis on comprehending the news spreaders, or the people who distribute news articles through posts on digital platforms, as a crucial component of this process. Numerous studies [58] on the news spread on digital platforms have focused on a variety of issues, including bias and political news, as well as the traits of the spreaders and their function in the dissemination process. Retweets, for instance, increasing the audience of URLs, as have been shown in studies on Twitter to significantly, by a factor of about two orders of magnitude. Additionally, for the better understanding, a number of studies are being conducted to the factors that affect how the sharing of news on social media platforms. A recent initiative has also addressed the issue of 'why are some news pieces shared more than others?' It was demonstrated by the researchers that the relevance of narrative important cues in promoting social sharing and the lower sharing of some themes (such as stories concerning politics, accidents, disasters, and crime). The reputation of users can be enhanced by sharing several topics. Recent studies have been motivated by this dynamic media interest as a result. Main reason why users share news. There is verity of factors which motivated users to share news on different social media platforms. It was included that the discovery of information, interpersonal interactions, entertainment, maintaining one's social status, and the intention to share news on previous digital platforms [59]. As stated by the studies, users are more likely to share news on digital platforms based on the uses and satisfactions that users derive from those websites and social intellectual theories who are motivated by the above-mentioned goals. Additionally important predictors of news sharing intention are personal interests and previous contact to digital stages [60] . User's patterns, engagement and behavior. Platforms of digital have increased the visibility and quantifiability of interpersonal interactions like never before. Users communicate with one another by following one other's updates and sending intriguing news to their pals. Users play a crucial role in this process since word-of-mouth propagation of this kind happens anytime a user passes information to friends of her. Unsurprisingly, numerous attempts have been made to comprehend users' roles in the ecosystem of news, focusing on news-sharing communities for example political, subscription of users and patterns of interaction, or even users social media relationships and influence of beliefs and on the spread of rumors [61]. However, technologies and users both are evolving continually. To Study users' methods of interaction and behavior is therefore a constant research topic.

Comments from users that interact. Digital platforms have evolved over the past several years into social hubs where users may connect and share their ideas, including the widely held beliefs or emotions about a particular piece of news [62]. Writing comments is now among the most popular ways that users connect with these collaborative systems. Many opportunities have been provided by online publications for involvement through comments and discussion forums. It was required to summarize and organize important comments based on factors like quality and investigate techniques for the distillation of sub-topics from all the comments connected to a with a query which was in the form of text to improve the user experience in these environments [63].

Along the introduction of various platforms of digital media into the news system, readers now have a variety of choices to determine where to get their news and what they want to see and read. Users will only be given a choice to a select various news based on groups of multiple news stories because of the way news rankings and feeds algorithms work. It is stated that, Facebook users, for instance, who are connected to individuals who have similar profiles, thus the news they receive tends to support their existed opinions. The term "echo chamber" refers to this phenomenon, which promotes the formation of social groups with same mind and the polarization of viewpoints. These suggestions include diversifying the news that users are reading or highlighting articles that attract similar responses from opposing political viewpoints [63]. The propagation of false information may encourage by the effect of echo chamber on social media platforms, as we'll cover in more detail in the sections that follow.

2.3 Fake News on Digital Platforms

Over time, the way news is disseminated has changed, from newspaper to radio set and TV, and more in recent times to digital platforms and internet journalism. Along with these changes, the overall ecology of news, including fake news, has also evolved. There are various social theories, psychological and cognitive frameworks, as well as research fake news effects on both individuals and the broader information ecosystem. Research has shown that people tend to prefer evidence which supports present beliefs of them [64]. Additionally, decisions are made by people based on the related drawback and benefits comparing to the current situation, as per research. Furthermore, readers often assume that their perception of reality is the only valid one and that anyone who disagrees with them is biased, uninformed, or irrational. All those features have a contribution for the ease of dissemination of fake news on web based media. While identification problem of fake news isn’t new, there have been recent advancements in the field that aim to better understand the occurrence of fake news on social media. A study by [1] in particular, it was found, false news spreads more rapidly than real news on social media. Another study by [65] examined the spread of false information on WhatsApp by analyzing political-oriented groups. In Brazil during significant social events, all the shared messages were collected, such as the Brazilian presidential campaign, and a national truck drivers' strike and it is found, among the shared content fake news was present. Based on they used an automatic procedure and labels provided by journalists. As [15] suggests a multidisciplinary task force as a solution to tackle such challenging issue. However, there are certain characteristics of digital platforms that contribute to the fake news spread. On digital platforms, it can be challenging to determine authenticity of users as some accounts may be fake. The low cost of creating an account on a digital platform has led to the creation of malicious accounts such as trolls and social bots, that are automated computer programs that communicate with non-bot users [66]. These bots are created with the intention of causing harm by spreading false information on digital networks. In US in 2016 The online discussion surrounding the presidential election social bots disrupted the discussions, and disinformation campaigns written by them as well during the 2017 French presidential election [67]. Recent research has shown that bots played a big role in the rapid spread of false information on platforms of news, by suggesting that modifiable social bots may be beneficial for the detection of fake news which is a very effective method. Platforms for digital media advertising have undergone significant advancements in recent years [67]. These platforms give marketers the ability to target particular user groups by taking into account personal data like name, email address, activities, ethnicity etc. millions of people’s personal information and activities access have been given worldwide in these platforms. However, malicious advertisers can also exploit targeted advertising to create social unrest, fuel grievances, and effectively reach those who are susceptible [67]. Digital media platforms have recently drawn attention to several ways in which Facebook's targeted advertising has been misused, including the improper disclosure of users' personal information to advertisers and the allowance of discriminatory advertising, such as excluding users based on their gender and race from seeing such kinds of ads. Additionally, new research from the Russian Intelligence Research Agency (IRA) in targeting susceptible populations with polarizing or controversial content has examined the effectiveness of ads related to politics, such as immigration and race-based policing, before the 2016 US presidential elections [68]. Overall, these findings suggest that social media advertising platforms can be exploited for malicious purposes, such as using targeted advertising to spread misinformation and create social unrest among vulnerable populations. One such phenomenon that has emerged as a result of digital platforms is the concept of echo chambers, where individuals are exposed to a homogenous set of information and ideas that reinforce their preexisting beliefs and attitudes, leading to a lack of exposure to opposing viewpoints and a reinforcement of misinformation.

2.4. Overview of Fake News

Digital platforms have been used by news organizations, and computer scientists are interested in them. However, the news media ecosystem is still changing quickly, and some of these developments encourage disinformation operations, exposing digital platforms as prospective and ideal spaces for propagating false information. Numerous fact-checking organizations, notably Boatos.org in Brazil and Snopes in other countries, have confirmed that the allegation is false. The fact-checking group Myth came to the precise conclusion that the only thing that can be stated with certainty is that citrus fruits may possibly contain anti-cancer chemicals that could aid in the prevention of cancer. It is important to note that there are currently no reputable medical or scientific studies that have confirmed neither lemons can effectively treat all types of cancer, nor have any well-known pharmaceutical companies reported that lemons are 10,000 times stronger than chemotherapy and able to destroy malignant (cancer) cells. These claims are not supported by scientific evidence and should be viewed with caution. It is important to always consult with a qualified healthcare professional and rely on credible scientific research when it comes to matters related to health. Previous research has identified at least three different categories of fake news. The first category includes sarcasm or imitation, where websites like ‘The Daily Mash or Onion’ post fabricated articles related to news as a form of humorous commentary on the media. For example, The Onion published an article claiming that in 2015 the Summer Cup in the US the FIFA corruption crisis would result [39]. Former FIFA Vice President Jack Warner was reportedly fooled by this satirical piece from The Onion.

The second category of fake news includes stories, tricks, and deceptive information that is not based on facts but supports a particular narrative. Although it is not true, it is still considered fake news because it is used in the wrong context. An instance of a damaging cross-platform attack is the fake news about the Columbian Chemical factory. The third category of fake news is one that has been deliberately fabricated using false information. These types of fake news are usually created and spread on digital platforms with the intention of generating revenue from clicks or confusing users. This thesis focuses on studying the third category of fake news.

2.4.1. Types of Fake News

The author [28] concentrated on three terms in the fake news problem: "Serious fabrications" have the traditional type of news, which is distributed on social media, "Large scale hoaxes" have the suspicious information that spreads properly on the broader scale and affects public thoughts, and "humorous fakes" have been written for the readers' amusement. However, Figure 6 defines the five primary categories of fake news.

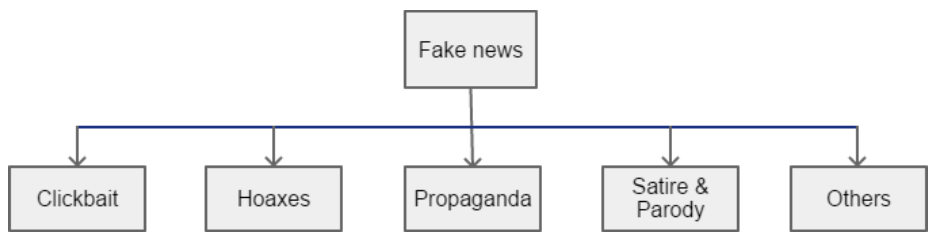

Figure 2.2: Types of fake news

Here, various fake news categories are described. Click bait is a false title in which the owner composes a news in order to capture the attention of the user. Owner receives when a user reads or views the story and clicks on the links, money is earned. The owner gets money on each click. A study demonstrates that users are more fascinated by click bait stories than headlines normally. They mislead the user by using click bait, which has nothing to do with actual headlines [39]. The majority of Macedonian youngsters have used click bait as Profitable industry [69]. A model for detecting click bait false news was given by the researcher and has an accuracy rate of 89.59% [70]. Hoaxes are false reports that cause purposely mislead the audience. This false information harms innocent people and destroys valuable documents. The reports of four Indonesian language sources were used by the writers to identify the hoax. By combining the PageRank algorithm and cosine similarity, they devised the Text Rank algorithm. The outcomes of this algorithm are astounding. False headlines are commonly utilized during times of conflict and are known as propaganda. In order to spread false information on how to stop the grave situation that led to the First and Second World Wars, the Journalist used propaganda. Propaganda is defined as "a news narrative for altering the public consciousness by political parties" according to researchers [71] . Fact checkers relying on experts can easily identify it. Satire and parody are two types of fake news that are frequently utilized to present the genuine story to the media in a comedic manner [72]. Satire presents the big picture on a grand scale, whereas humor imitates another person. Despite the fact that the goals of both satire and parody are to inform and entertain, however, parody contains misleading information whereas satire contains genuine information. Satire, according to the researcher, is humor that amplifies facts for the audience [71] . Name-Theft is a type of fake news in which a person takes credit for a real news outlet in order to mislead the audience. Without realizing the stations' false identities, people believe this bogus news source. Another type of fake news called framing involves the user providing objective facts. While the reality was hidden, some substance of certainty was displayed.

False news seriously harms a person's reputation and sense of worth. To address this issue, several research investigations are done. The detection of fake news uses a variety of machine learning, ensemble learning, and deep learning based techniques. Other feature engineering-based strategies are also employed for false news detection and produce better results than earlier studies. Our primary goal is to use machine learning and statistics to address the issue of fake news datasets.

2.5 Fake News Challenges

Challenges: Detecting false news has proven to be a difficult and time-consuming task. Scholars from all over the world are particularly interested in whether a news story, blog post or other online content is authentic or fake. The news can create an immense impact on people's opinions and behaviors. Fake news has become a significant problem [4]. Dealing with fake news is a difficult and challenging process. Fake news has a tremendous and growing impact on the social and political environment. The internet has altered how people share their thoughts. Online reviews include remarks, tweets, postings, and comments on various online platforms, such as news and review websites, e-commerce websites, and social networking sites.

As individuals spend so much time on social media and access online sources of information. So, determining the reliability of news has become challenging [15]. Though fake news is an old problem, political and other parties have been using the social media for news to carry out Impact and publicity in favor of their personal objectives. The evolving of internet news on web media has enhanced the impression of fake news, challenging traditional journalistic standards. People obtain the majority of their information through these channels since it is free and accessible from any location at any time. Because this content can be distributed by anybody, it lacks responsibility, making it less trustworthy than traditional ways of gathering information such as newspapers or verified sources.

2.6 Background

The Fake News Challenge is seen as a significant first stage in detecting false news and investigating how AI capabilities can be used to address it. It is suggested by the organizers that journalists primarily require a semi-automated tool that may help them in identifying potential sources of Fake news instead of having a completely automated workflow which already determines the truth of a news piece itself. Furthermore, building a fully automated pipeline is very difficult because identifying fake news needs fact-checking which, depending on the claim and the topic, may require detailed research. The FNC concentration is determining the relationship between various article bodies and a brief claim reporting on this claim because manual fact-checking will likely still be required in the future. What are various news organizations reporting about given a certain claim about a topic? It can be assumed that a claim is true if it is supported by the majority of news organizations. On the other hand, if many of news media reject the claim, it is probably false. This idea is statistically turned into a stance identification task. In which the argument is treated as a headline and the "stance" of the article body is either Agree, Unrelated, Discuss, or Disagree. Further classified as Related are the first three labels. In the end, fake news detection is thus tackled as a classification problem with four groups that are regarded as the stance of an article body towards a specific claim of headline.

2.7 Detection Problems

A number of new and complex research issues surround the identification of fake news on social media. Fake News is a more potent force that threatens traditional journalistic practices as web-generated news on social media becomes more popular [73]. Here is a list of the issues brought on by fake news. First of all, fake news aims to deceive people into reading information that contains hard to identify fraud and misleading content. The majority of the time, this content uses linguistic techniques to appear as true news while covering a variety of subjects and writing styles. We must make use of additional information provided, such as social interaction, meta-data, etc., to address this issue. Secondly, another issue arises by exploiting this additional info: the data quality. Because fake news relies on brief news bursts and temporal events, which cannot be fully checked by knowledge bases or specialists, a lot of noisy, unstructured information is being produced, which creates a Big Data challenge.

2.8 Motivation

Over one-third of people on the planet actively utilize digital platforms, such as social media networks and messaging programs [74]. Through the launching of a flood of new applications and the alteration of current information ecosystems, these platforms have fundamentally changed how people engage and communicate online. Digital platforms in particular have fundamentally altered how news is generated, transmitted, and consumed, offering both unexpected opportunities and challenging new problems.

These digital platforms' very nature is one of the reasons for this transition. In comparison to traditional news outlets like newspapers or television, producing and consuming news on digital platforms is frequently timelier and less expensive. It is also simpler to share, comment on, and engage in discussion about the news with friends or other readers. digital platforms, which improve user interactions and communication [73]. As a result, online platforms are influencing how individuals consume information.

These platforms have a lot to offer our society, but despite this, they have also become a location for misinformation campaigns that frequently aim to mislead individuals, especially in areas like politics and health.

There is irreversible harm being done to people's health as a result of the massive amount of false medical information being shared on internet platforms. An online advertisement for an experimental cancer treatment, for instance, was misinterpreted by a cancer patient as medically accurate information, which led to his demise [75].

1. An increase in rumors and conspiracies have been circulating on social media during the pandemic of COVID 19 [76]. In less than two months, the International Fact-Checking Network discovered more than 3,500 untrue claims on COVID-19 [35]. As a result, in the first three months of 2020 it's possible that 800 or more individuals perished globally due to false information about the coronavirus.
2. In environment of politics, election after election, we may see numerous forms of wrongdoing and complicated techniques of opinion manipulation through the distribution of fake news. The presidential election 2016 in USA is still recognized for a misinformation war that primarily took place on Facebook and Twitter. The infamous case was a Russian attempt to sway events through carefully targeted advertising [68] . Similar attempts were made during the Brazilian elections of 2018, when WhatsApp was used to spread misinformation campaigns and a lot of modified photographs and memes with various political insults were utilized. According to a recent study, 88% of the most shared photos during the final month leading up to the Brazilian elections were either fraudulent or deceptive [77].

3. In India, where WhatsApp was also used, false stories that were propagated via the website were to blame for a number of lynching's and social disturbances [78].
4. The ability for anyone to sign up and serve as a news publisher on digital platforms without paying any fees is a distinctive feature that fosters the phenomena of false news (e.g., Anyone can start a WhatsApp group or a Facebook page pretending to be a newspaper or news group and providing information there.).
5. As a result, not only are conventional news organizations moving more and more to digital media, but numerous new news sources are also appearing on these platforms.
6. For instance, prior research revealed that in the United States in 2018 there were over 20,000 Facebook pages classified as news publishers [48].

With this transformation, worries are growing related to fake news producers that publish and create fake news articles, frequently spreading fake news widely through on the platforms of social media [15]. For example, during the last weeks of the 2018 election, a survey supported by Avaaz6 questioned Brazilian voters if they had seen and believed some of the most prevalent false news stories on different web-based platforms. Impressively, findings showed that more than 98% of voters surveyed had come across one or more false news pieces.

2.9 Summary

Titled "Background," sets the groundwork to understand fake news detection better. It's like building the foundation of a house. The chapter explains what fake news is and how it spreads on digital platforms. It also talks about how news works in the digital world - how it's made, how people read it, and how it's shared. This is important because fake news acts differently online than in traditional media. The chapter explains different types of fake news and the problems in finding them. It tells us why it's not easy to find fake news, like tricky tactics and technology challenges. Lastly, it explains why it's important to study and detect fake news, as it can affect how people think and make decisions. This chapter gives us the knowledge base to tackle fake news effectively.

CHAPTER 3

LITERATURE REVIEW

3.1 Related Work

We have discussed some of the most popular machine-learning techniques for classifying fake news in this section that have previously been developed and presented by other experts. We are going deeper and sharing the relevant work from other authors and researchers because we have previously addressed the unresolved issues that were brought on by fake news. The majority of them concentrate on finding fake news by using machine learning algorithms and deep learning methods. We considered not only natural language processing and machine learning but also statistical techniques.

Ribeiro et al; [10] trained four machine learning classifiers, KNN, decision tree, SVM, and random forest. The fake news dataset was download from Kaggle. Id, title, text, and label are the four features of the dataset. There are 7796 entries in the dataset. 6335 rows of data are taken into account for analysis after preprocessing. The data set is split into a test set and training set. Out of 6335 records, 1901 components have used as the test set, while 4434 entries are used as the training set. They successfully create a model to identify fake news from the provided datasets by applying the algorithms. For text preprocessing they used NLP techniques. SVM provides the lowest accuracy among all classifiers, while random forest provides the highest accuracy. Programming in Python was used to carry out experiments.

Ahmed et al; [79] used n-gram analysis and several feature extraction methods, the author built a detection model for fake news. The main dataset utilized in this study was created by the authors' team by combining publically available news articles. Additionally, they put their model to the test using the publically available data set Horne and Adali's. Furthermore, they suggested a model for detecting fake news that makes use of machine learning and n-gram analysis. They examine and contrast six different machine classification techniques as well as two different feature extraction techniques. Using the feature extraction method Term Frequency-Inverted Document Frequency (TF-IDF) and the classifier Linear Support Vector Machine (LSVM), got an accuracy of 89%, which produce best performance in experimental evaluation.

To identify fake news, the author Ahmed et al; in [80] utilised three classifiers “Naive Bayes, Support Vector Machine, and Passive Aggressive. They used machine learning algorithms for this. Since classification techniques are not perfectly suited for detecting fake news, so simple classification is not entirely accurate. Fake news identification and creating algorithms which can identify the data of news by combining machine learning and text-based processing. They used classifiers that can categorise the news data and detect fake news. According to their proposed method, machine learning techniques should be used to differentiate between fake and real news pieces. The created system's accuracy of up to 88% shows how important the combination of Natural Languages Processing techniques and machine learning classifiers is.

Hirakata et al; [81] proposed a method to identify fake news, but the volume of records on social media and on the internet has grown significantly in recent years, making it difficult and time-consuming to identify whether a part of info is fake or real. Instead, they use classification techniques to sort through the massive amounts of data. Here, they suggested a classification-based false news detection system using techniques like Naive Bayes (NB), Logistic regression (LR), Random forests (RF), Support vector machines (SVM), and deep neural networks (DNN). All machine learning methods for identifying fake news were compared. After comparing LR, RF, NB, SVM, and DNN in terms of memory, time, and accuracy, the comparison results show that DNN is better than all of the algorithms in terms of time kind and accuracy because the rest of the methods need further time and provide low accuracy, so DNN played important role than all of the classifier to identify fake news.

Author conducted an in-depth analysis of several machine learning classifiers, such as Naive Bayes, Support Vector Machine and Logistic Regression, and their performance when utilizing tokenization as a feature. Tokenization is a process of breaking down a sentence into individual words, also known as tokens, in machine learning these can be used as features. The author compared the performance of these classifiers using tokenization as a feature and recommended a method for optimizing system efficiency. After conducting experiments and evaluating the results, the author found that using the Naive Bayes classifier resulted in the highest level of efficiency. However, it is essential to note that the model's accuracy was only 81.25%, which may not be sufficient for certain applications. This suggests that further improvements to the model may be necessary for the purpose of improving outcomes [82].

Mahir et al; [83], conducted a comparison between deep learning techniques and machine learning. To do so, they develop models using three popular natural language processing techniques: Count Vector, TF-IDF, and Word Embedding. Of the models tested, the author found that the Support Vector Model (SVM) performed the best, achieving an efficiency of 89.34%. This suggests that the SVM was particularly effective at classifying the data used in the study. Additionally, the author's comparison of deep learning (DL) and machine learning (ML) highlights the effectiveness of these techniques in natural language processing tasks. However, the author did not specify the dataset, task or the context of the comparison, which makes it hard to draw a conclusion based on the result.

Srivastava et at; [84] and Sharma et at; [7] suggested a method, in order to determine if news is real or fake, on a real - time basis. Natural language processing known as NLP has been used to extract features from the input data. These characteristics are then used to train the classifiers of machine learning like Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Naive Bayes, Stochastic Gradient Descent (SGD), and The efficiency of each classifier is measured using several metrics. Then the best performing classifier is deployed as a website using flask API for real-time prediction of the news.

Granik et al; presents a process for identifying incorrect news by utilizing a Naive Bayes Classifier. The technique was tested using a dataset of Facebook news posts and the Buzz Feed news dataset. The results of the test showed a classification accuracy of approximately 74%. This means that the Naive Bayes Classifier, when trained on this dataset, was able to correctly identify false news posts with a high degree of accuracy. The use of multiple datasets, such as the Facebook and Buzz Feed news datasets, provides a more robust evaluation of the method, as it allows for the testing of the classifier on a diverse range of news content. The high classification accuracy also suggests that Naive Bayes (NB) algorithm is a promising approach for detecting false news [85].

In the study Gadekar et al; [86] described two famous machine learning classifiers used, Support Vector Machine (SVM) and the Naive Bayes classifier, to classify a dataset. The authors used these two classifiers to classify their dataset and obtained an accuracy of 60.97% with the SVM classifier and 59.76% accuracy with the Naive Bayes classifier. This indicates that both algorithms performed similarly on the dataset and that the SVM classifier had a slight edge in terms of accuracy. The authors may have also considered other assessment metrics such as F1-score, precision, and recall to estimate the effectiveness of the classifiers. However, it should be noted that these results are specific to the dataset used in the study and may not be generalizable to other datasets or tasks.

Bhutani et al; focused on the key feature like sentiment for detection of fake news. To achieve this, they employed three separate datasets for their experiments. They used several techniques to pre-process the data, including cosine similarity, Tf-Idf vectorizer, Count vectorizer, and the use of Bi-grams and Trigrams. In natural language processing, to extract features from text data, above mentioned techniques are commonly used. The authors then trained their model using two popular machine learning algorithms Random Forest and Naive Bayes. Naive Bayes is a simple probabilistic algorithm that is often used in text classification tasks, while Random Forest is an ensemble learning method that combines multiple decision trees to improve the accuracy of the model. The authors evaluated the performance of their model using several performance indicators. They reported an accuracy of 81.6%, which suggests that their model was able to effectively identify fake news [87].

Gottfried et al; [12], the authors suggested a model for real-time prediction of news articles being real or fake. NLP based system in which techniques are used to for the feature extraction from the news articles, such as the presence of certain keywords or the sentiment of the text. These extracted features are then used as input to various ML classifiers like Support Vector Machine (SVM), Random Forest, Naive Bayes, and Logistic Regression. To predict the given news is fake or real, it is proposed that the model used these classifiers. The use of NLP techniques to extract features and the use of multiple classifiers in an ensemble method enhanced the accuracy and robustness of the model. The author claims that this model is suitable for real-time prediction, which means that it can process and classify news articles in near real-time, providing useful results quickly.

Brașoveanu et al; [88] combined natural language processing, semantics, and machine learning. They presented a new semantic fake news detection technique that uses relational variables like entities, sentiment, or facts that are directly derived from text. Their study shows that by including semantic characteristics, the categorization of fake news is much more accurate. Their findings show that adding relational features, such as, facts drawn, named entities or sentiment, from both unstructured (such as text) data and structured (for example knowledge graphs) and, often improves classifier performance.

Agarwal et al; [89] pointed the issue of classifying labelled news statements using natural language processing techniques and machine learning. For this, they employed a variety of text extraction and representation methods such as bag-of-words, TF-IDF (term frequency-inverse document frequency), n-grams, and count vectorizer method to convert the news statements into numerical feature vectors. These feature vectors were then used to train five different ML classifiers, which were used to detect the class labels of the news statements. The authors acknowledged that the dataset used in the study is irregular, which means that it may contain anomalies and outliers that can affect the performance of the prediction models. To this problem, it is kind of limitations that come along with.

Bali et al; [90] described, the problem has been discussed from the perspectives of machine learning and natural language processing. From the headlines, the features were collected and the contents are used in the evaluation of three conventional datasets. The accuracy and F1 scores of the seven machine learning methods are compared. With a mean accuracy of 88%, Gradient Boosting outperformed than other classifiers.

Lazer et al; used two pre-training vectorizing algorithms, CountVectorizer and TF-IDF models and five fine-tuning techniques were employed, neural networks (such as LSTMs and ANNs) achieve better than other classifiers [15]. Srivastava et al; [91] integrated strategy that combines machine learning, semantics, and natural language processing is needed to solve the problem of inferring information about the many parties involved in a news item. The author proposed a semantic method for identifying false news that is based on relational properties like sentiment, entities, or facts that may be directly derived from text. Author concentrate on brief texts with varying degrees of truth, demonstrating that the addition of semantic characteristics considerably increases accuracy. For the purpose of fully using the connections between the entities mentioned in a press release, author proposed new procedure which include the following main steps which was metadata collection, relation extraction and embedding's.

Ivancová et al; [92] main area of interest was identifying fake news in Slovak-language news items. They developed a labelled dataset made up of political news stories published by online news portals as well as suspicious conspiratorial portals in order to successfully train deep learning models. Using this data, they trained two deep learning models i.e CNN and LSTM neural networks architectures. Standard classification matrices were used in an experimental evaluation of the models' performance. The accuracy of CNN model was 92.38 % and recall metric was 90% and with precision of 91%. LSTM model accuracy of 91.56%.

Meesad et al; [93] described a framework for effective Thai fake news identification is proposed by the author. Their methodology consists of two methods. First, use information retrieval to get information from social media and an online news website. The news is then analysed using natural language processing, producing well-differentiated feature data. Finally, after receiving the feature data, machine learning divides the news stories into three categories: real, fake, and questionable. We pre-classified the data for 41,448 samples into real, fake, and suspicious groups using a web crawler to crawl the data. There are an equal number of data samples in each group.

The framework is made up of three major modules: information retrieval, natural language processing, and machine learning. The two main parts of the study was data collecting and creating machine learning models in order to extract useful features from web data, they used natural language processing techniques to examine data that we had collected from Thai online news websites utilising web-crawler information retrieval. They have chased a number of popular classification machine learning models for comparison, including Nave Bayesian, Logistic Regression, K-Nearest Neighbour, Multilayer Perceptron, Support Vector Machine, Decision Tree, Random Forest, Rule-Based Classifier, and Long Short-Term Memory. Long Short-Term.

Table 3.1: Comparison of Existing work of Machine Learning Approaches

Refer.	**Features**	**Method/Algorithm**	**Results**	**Remarks**
2019 [1]	N-gram	KNN, SVM, decision tree and random forest	Accuracy 87%	Random forest shows good result
2017 [2]	TF-IDF, N-grams	Linear Support Vector Machines	Accuracy 89%	KNN produced the lowest accuracy of 47.2%

2020 [3]	Count Vectorizer, TF-IDF	Passive Aggressive, Naïve Bayes, and Support Vector Machine	Accuracy 90%	Passive Aggressive Shows high accuracy
2019 [4]	Bag of words and TF-IDF	Logistic regression (LR) , Naive Bayes (NB), Random forest (RF), Support vector machine (SVM), and deep neural network (DNN)	Accuracy 90%	Where DNN's accuracy is better to that of the other four algorithms
2019 [5]	Bag of Words	Support Vector Machine, Naive Bayes, and Logistic Regression	Accuracy 83.25%	NB with Higher Accuracy
2019 [6]	Count Vector, TFIDF, and Word Embedding	Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Logistic Regression, Naive Bayes, SVM	Accuracy 76% Accuracy 89.34	SVM is the most effective categorization approach
2020 [7]	Bag of Words, TF-IDF	Logistic Regression (LR) Random Forest (RF), Support Vector Machine (SVM), Stochastic Gradient Descent (SGD) and Naive Bayes,	Accuracy 89%	Support Vector Machine classifier with TF-IDF a is the best performer in terms of accuracy
2017 [8]	Bag of words	Naive Bayes	Accuracy 74%	Low Accuracy
2019 [10]	TF-IDF	SVM Naive Bayes	Accuracy 60.97% 59.76%	Low Accuracy

2019 [11]	Tf-Idf vectorizer, the Count vectorizer	Naive Bayes Random forest	Accuracy 81.6%	RF Performs better than NB
2019 [12]	sentiment, entities	ML Classifiers	Accuracy 83%	SVM performed better than other classifiers
2019 [13]	n-grams and bag of words	, Logistic Regression, Random Forest Classifiers, Naïve Bayes Stochastic Gradient Classifier and Linear SVM	F1 Score 0.61	Random Forest Classifiers outperformed other classifiers
2019 [14]	Bag of Words TF-IDF	Seven machine learning algorithms	accuracy of 88%	Gradient Boosting outperformed other classifiers
2020 [15]	CountVectorizer, TF-IDF	LSTMs, , Logistic, Random forest ,ANNs, SVM algorithms	accuracy of 91%	ANNs and LSTMs perform better than other neural networks.
2021 [94]	CountVectorizer TF	NB and LSTM	Accuracy Of 89% and 90%	LSTM Performs better
2022 [95]	TFIDF N-grams	Bi-LSTM LSTM	Accuracy of 91% and 90%	Bi-LSTM Performs better
2022 [91]	TF-IDF Bag of words	Voting Classifier Bagging meta-estimator (DT) Bagging meta-estimator (ensembled model)	0.851 0.80 0.86 0.84 0.75	ensembled model performs better than all other classification methods

		Adaboost (ensembled model) Gradient boosting (ensemble model)		

3.2 Summary

In Chapter 3, called "Literature Review," we look at what other researchers have already studied about fake news detection. This part focuses on a section titled "Related Work," where we explore the research that has been done before. We see what other people have found out about detecting fake news. This helps us understand the different methods and ideas that have been tried. By looking at what others have done, we can figure out what works well and what might need improvement. This also helps us come up with new and better ways to detect fake news. It's like learning from others' experiences to make our approach smarter and more effective.

CHAPTER 4

METHODOLOGY

4.1 Overview

The dataset was downloaded from Kaggle (WilliamLifferth, 2018), which contained noisy or irrelevant text data. To clean and standardize the text data, several preprocessing techniques were applied. Stop words, which are common words that do not carry much meaning in a sentence (e.g., ‘the,’ ‘and,’ ‘a’), were removed. Tokenization was used to split the text into individual words or tokens. Stemming and lemmatization were used to reduce the inflected or derived words to their base form, and lower casing was used to standardize the case of all the words. After preprocessing, the study used the TF-IDF technique to extract features from the text data. TF-IDF assigns a weight to each word based on how frequently it appears in a document and how rare it is across all documents. This technique allowed the study to identify important and informative words that are features of each document or category. Finally, ML and statistical techniques were applied to classify the text data based on the extracted features. Figure below shows the steps of deployed model.

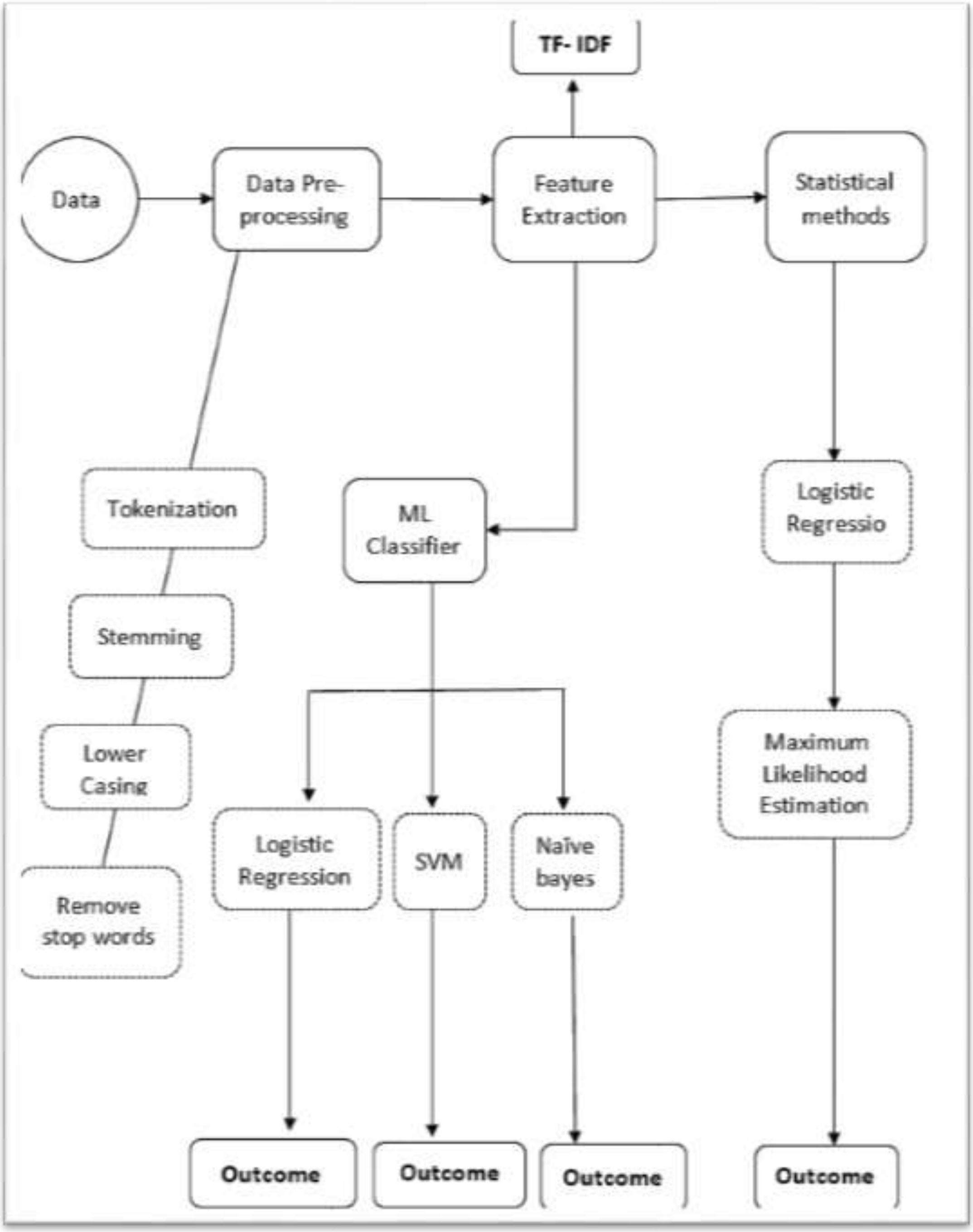

Figure 4.1: Steps of Experiment

4.2 Natural Languages Processing

An overview of text processing, including the representation of natural language inputs and outputs, is discussed in this section. As we know Machine learning classifiers don't interact directly with the text. The documents must be changed into a representation that machine learning classifiers can understand and process them. Natural Language Processing is a field in linguistics, computer science, data engineering, and artificial intelligence [96] that is concerned with language processing. NLP is concerned with how people and computers communicate. Numerous natural language data sets can be processed and analyzed using NLP. There are numerous uses for NLP, including text classification, Chabot's, intelligence, speech recognition, autonomous question and answer production, sentiment analysis, and machine translation. Text extraction is a fundamental step in natural language processing (NLP), used as a preprocessing step before performing classification or other machine learning tasks [97]. Tokenization, Stop words removing, word stemming, term frequency, and lower casing are all fundamental NLP preprocessing steps [98].

4.3 Data Pre-Processing

In machine learning, preprocessing involves preparing and transforming data into a format that can be easily fed into a model for training. Effective preprocessing can significantly improve the performance of a machine learning model by ensuring that the data is in a suitable format for analysis and modeling. Real-world data is frequently insufficient, inconsistent and tends to have many errors, and is often incomplete. An effective way to address these problems is through data preparation. These data preprocessing techniques include Lowercasing, stop word removal, Stemming, and lemmatization as shown in figure 7.

- **Features reduction**

In my research context of fake news detection using a combination of statistical techniques and machine learning, the process of feature reduction involved the following steps:

1. Feature Extraction: Initially, I extracted a set of features from the raw text data using methods like TF-IDF. This generated a high-dimensional feature space where each word or phrase became a feature.

2. Feature Analysis: Before reducing features, it was crucial to analyze their relevance and importance. I used statistical methods like correlation analysis or mutual information to identify features that were highly correlated with the target variable (fake or genuine news) or had strong predictive power.

3. Outlier Removal with MLE: During the process, I employed Maximum Likelihood Estimation (MLE) to fit the model parameters. This also had the advantage of automatically identifying and removing outliers in the data, contributing to a cleaner and more accurate dataset.

4. Evaluation: The final set of reduced features was evaluated using various performance metrics like accuracy, precision, recall, F1-score, etc. I aimed to strike a balance between feature reduction and maintaining or improving model performance.

By iteratively applying these steps, I was able to gradually reduce the number of features while retaining the most informative ones for my fake news detection model. The specific methods I used depended on the characteristics of my dataset, the chosen machine learning algorithm, and the desired level of model interpretability and generalisation.

The following actions are typically carried out for better results:

- **Steps of Pre-processing**

The raw data must first be processed before evaluating the model's overall performance. The number of data pre-processing steps was reduced to the minimum.

4.3.1. Tokenization

Tokenizer typically make some form of trade-off between having a very flexible word-based tokenization vs a more effective character-based tokenization. It was decided not to do lower-casing because every tokenizer has the ability to process case-sensitive text. The NLTK word tokenizer was used to filter the text before feeding it to the tokenizers in order to eliminate stop words.

4.3.2. Stop Words

Typically, stop words are eliminated during NLP pre-processing. Any term that is perceived to be meaningless and that is used frequently is a stop word. These are the terms that are employed in all languages to indicate the tenses of sentences or to link words together. This indicates that even after deleting the stop words, we can still understand the context if we use these words in any sentence because they do not significantly add to the content of the statement. The most frequent keywords in a language are frequently referred to as "stop words," although all-natural language processing techniques don't employ a single, comprehensive list of stop words.

The Natural Language Toolkit, or more generally referred to as NLTK, is a collection of Python-coded tools and applications for statistical and symbolic natural language processing of English. These packages include text processing operations like tokenization, parsing, categorization, stemming, tagging, and semantic reasoning. Too-frequently used words that are not considered informative

Examples:

The, an, a, at etc.

4.3.3. Stemming/Lemmatization

Replace the word or token with its Base form and the process by which suffixes are eliminated from words to produce the "word stem." For instance, the word "like," which is derived from the phrases "likes," "likely," and "liked," can be used as a synonym for all three words. In this method, an NLP model can identify that all three words share some similarities and are used in comparable situations.

Another Example

Stay, Stays, Staying, Stayed -> Stay

House, Houses, Housing -> House

4.3.4. Lower Case Conversion

We now have changed all the capital words to lowercase after the words have been tokenized and the punctuation removed. All data should be converted to lowercase as this will help in preprocessing and later analyzing stages of the NLP application.

For example

```
def wordlowercase():
    text= "I am a person. Do you know what is time now?"
    print text.lower()
```

The outcome of the above snippet of code after changing the case is as follows:

'I am a person. do you know what is time now?'

4.4. Words to Vectors Conversion

The input to our machine learning model is text. The algorithms are unable to directly understand the text. So after preprocessing our data, we have converted text into vectors or numbers.

In order for machine learning algorithms to understand our data, Vectorizing is the act of encoding text as integers, or numeric representation.

4.4.1. Vectorizing Data: Bag-Of-Words

The frequency of words inside the text data is described by Bag of Words (BoW) or Count Vectorizer. If it is in the sentence, it returns a result of 1, else it returns a result of 0. As a result, each text document is converted into a bag of words with a document-matrix count.

4.4.2. Vectorizing Data: TF-IDF

The TF-IDF weight describes the overall importance of a words in the document and the full corpus by measuring the "relative frequency" compared to how frequently a word appears in all documents combined. The phrase "Term Frequency" (abbreviated "TF") indicates how frequently a term appears in a document. Because document sizes vary, a term may appear more frequently in a lengthy text than in a brief one. As a result, term frequency is usually split by document length.

$$\text{TF (t)} = \frac{number\ of\ term\ t\ occurrence\ in\ a\ document}{total\ number\ of\ terms} \quad (1)$$

IDF stands for Inverse Document Frequency: If a word appears in every document, it is of little use. In a paper, certain words like "a," "an," "the," "on," "of," etc. repeatedly appear yet have little meaning. IDF gives less value to common phrases and more weight to unique ones. The uniqueness of the word increases with IDF value [17].

$$\text{IDF (t)} = \ln \left(\frac{total\ number\ of\ documents}{total\ number\ of\ documents\ with\ term}\right) \quad (2)$$

After applying TF-IDF to the body text, the document matrix preserves the relative count of each word in the sentences.

$$\text{TFIDF (t, d)} = \text{TF (t, d)} * \text{IDF (t)}$$

4.5. Feature Extraction Process

Machine learning algorithms used a predefined set of features from the training data to provide results for the test data. The fundamental issue with language processing, however, is that machine learning methods cannot directly work on the raw text. Therefore, some feature extraction techniques are required in order to turn text into a matrix (or vector) of features, the most well-liked feature extraction techniques include:

- **TF-IDF**

a. Term Frequency (TF)

TF stands for Term Frequency. This method involves counting the number of times words appear in a document to determine the similarity between documents.

- tf-idf(t, d) = tf(t, d) * idf(t)

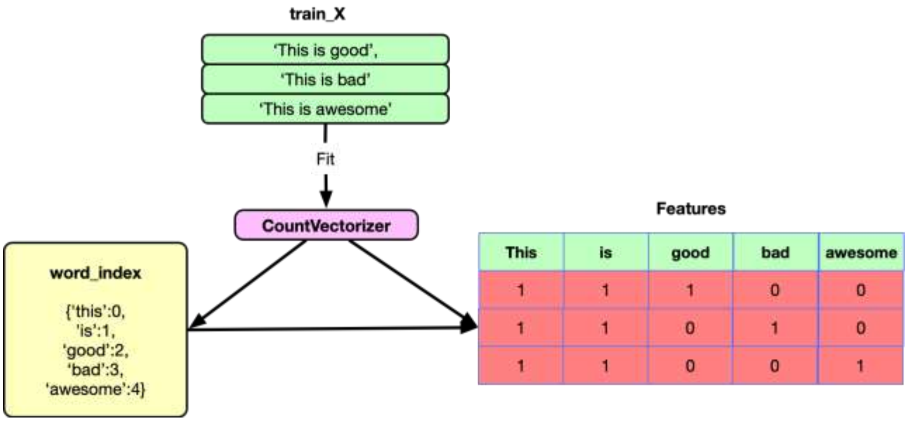

Figure 4.2: Feature Engineering Process

b. Term Frequency-Inverted Document Frequency (TF-IDF)

TF-IDF is a weight measurement frequently applied in natural language processing and information retrieval. This statistical metric determines the significance of a term in a document dataset. The formula for calculating TF-IDF is:

- tf(t,d)=log(1+freq(t,d)
- idf(tD)=log log (Ncount (dεD:tεd))

It is an easy and adaptable way to extract features from documents. A text representation that describes the frequency of words in the document is known as a count vectorizer model. We don't pay attention to grammatical rules or word order; we only keep track of word counts.

```
Out[26]: ['abandon',
          'abc',
          'abc news',
          'abduct',
          'abe',
          'abedin',
          'abl',
          'abort',
          'abroad',
          'absolut',
          'abstain',
          'absurd',
          'abus',
          'abus new',
          'abus new york',
          'academi',
          'accept',
          'access',
          'access pipelin',
          'access pipelin protest']
```

Figure 4.3: Tokenized Words

	abandon	abc	abc news	abduct	abe	abedin	abl	abort	abroad	absolut	...	zero	zika	zika viru	zionist	zone	zone new	zone new york	zoo	zu	zuckerberg
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0	0	0	0	0	0	0

5 rows × 5000 columns

Figure 4.4: Extracted Features from the dataset

- **Using a dictionary of 5000 features (terms) in the context of fake news detection**

1. Rich Vocabulary Representation:

A dictionary of 5000 features covers a diverse range of words that commonly appear in news articles. This allows the model to capture semantic nuances and linguistic patterns indicative of fake or real news.

2. Effective Information Capture:

While larger dictionaries might offer more granularity, they can also introduce noise and increase computational complexity. A 5000term dictionary strikes a practical balance, capturing key information without overwhelming the model.

3. Computational Efficiency:

Larger feature sets demand more computational resources for processing and training. A dictionary with 5000 features is manageable and ensures efficient training and inference, making the system more practical for real time applications.

4. Reduced Risk of Overfitting:

Using an extremely large dictionary could lead to overfitting, where the model learns noise present in the data. A dictionary of 5000 features mitigates this risk, promoting better generalization to new, unseen data.

5. Interpretability:

A dictionary of 5000 features allows for meaningful interpretation of the model's decisions. The selected terms contribute to the understanding of why the model classifies certain news articles as fake or real.

6. Data Imbalance Handling:

In fake news detection, datasets can be imbalanced, with more instances of one class than the other. A balanced dictionary helps prevent bias towards the majority class and enhances the model's ability to detect both fake and real news.

7. Resource Allocation:

Developing and maintaining a dictionary requires time and effort. A dictionary with 5000 features offers a good trade-off between resource investment and the performance boost gained from feature extraction.

In conclusion, a dictionary of 5000 features strikes a practical and efficient balance between comprehensiveness and manageability. It enables effective representation of news articles while addressing challenges related to computation, overfitting, and interpretability in the context of fake news detection.

4.3.1. Tokenization

Breaking down phrases into words; Tokenization, the process of separating a text or collection of texts into individual words, is a typical NLP task. For ease of understanding, we changed certain words to their most basic forms [99]. The process of breaking down a sentence into a stream of words, or "tokens" is called Tokenization. The foundational elements on which analysis and other techniques are constructed are tokens. Many NLP toolkits allow users to enter various parameters that are used to establish word boundaries. To tell if one word ends and the following one starts, for instance, you can use whitespace or punctuation. Again, these rules may not always apply. For instance, words like don't, it's, etc. contain punctuation on their own and must be handled independently.

4.3.2. Removing Stop words

Stop word removal have been used because it eliminates Common and unwanted words used in news articles, conjunctions, and prepositions [100]. Eliminating/Removing useless words that have little or no impact on meaning, such as "the" and "is," etc. and punctuation, tags, etc. as well; Preprocessing in NLP typically entails removing words called stop words. Any word that is regarded as carrying no information and appearing unusually frequently is a stop word.

4.3.3. Stemming

Getting the base of words by eliminating extra characters, typically the suffix. The natural language characteristic has a significant impact on this phase. Stemming is the reduction of a word to its base or root term. For instance, the phrases ‘connecting,’ ‘connect,’ ‘connection,’ and ‘connects’ are all reduced to the root form word ‘connect.’ The word ‘studi’ replaces the words ‘studying,’ ‘studies,’ and ‘study.’ Stemming is also applied during the preprocessing step in text classification and emotion recognition.

4.3.4. Lemmatization

A more advanced variation of stemming includes changing each word to its "lemma," or equivalent root form. However, not all words produced through stemming are included in the language's vocabulary. It frequently leads to words that the users don't understand. We have applied the concept of lemmatization in order to get around this problem.

4.3.5. Lower Casing

When we have a text input, like a paragraph, we often see words written in both lowercase and uppercase. However, the same words written in different cases are treated as different entities by the computer. For instance, while having the same meaning, the computer treats the terms "Girl" and "girl" as two different words. We have changed all the words to lowercase to fix this problem. In NLP software, lowercasing is the most popular approach.

4.4 Words to Vectors Conversion and Feature Engineering

The next stage was to encode words as vectors or numerical values. Feature engineering is the procedure that specifically extracts those features from an experiment that produces high quality findings. Here, various feature extraction methodologies have been defined.

4.4.1. TFIDF

TFIDF, also referred to as Term Frequency Inverse Document Frequency uses the BOW technique for the purpose of feature extraction. The BOW method is simple and works well, but there's a problem with BOW: it treats all words equally. As a result, it cannot differentiate between very common words and rare words. So, to overcome this problem, TFIDF comes into the picture. It is used to illustrate the importance of a word or phrase in a particular paper.

The two components of TFIDF Vectors are TF, which stands for Term Frequency & IDF, which is defined as formulas:

TF (t) = number of term t occurrence in a document total number of terms

IDF (t) = ln (total number of documents total number of documents with term)

Different levels of matrix representation

- Words level shows the terms' TFIDF scores;
- Ngram level – indicates Ngram TFIDF scores;
- Character level shows character level ngrams' TFIDF scores;

4.5 Classifiers

Machine learning refers to the development of algorithms and statistical models that can learn from data without being explicitly programmed, and that can use this learned knowledge to make predictions or take actions. The objective of machine learning is to enable computers to automatically identify patterns and relationships in data.

4.5.1. Naive Bayes

The Naive Bayes algorithm uses the Bayes theorem as the foundation for its supervised learning approach to classification problems. It is mostly employed in text categorization using a sizable training set. One of the simplest and effective classifiers is the naive Bayes algorithm, which helps in creating speedy machine learning models that can generate predictions quickly. Multinomial Naive Bayes uses the frequency of the words as a feature to classify the data in various classes.

P (class | features) = (P (features | class) * P (class)) / P (features)

The main principle of Naive Bayes is all features in the data is independent of every other feature, meaning that the absence or presence of one feature has no bearing on the likelihood of any other feature. The "naive" assumption, which goes by this name, enables the algorithm to generate predictions very quickly.

Naive Bayes' simplicity and ease of use are two of its primary features. It is an excellent option for many real-world applications.

4.5.2. Support Vector Machine

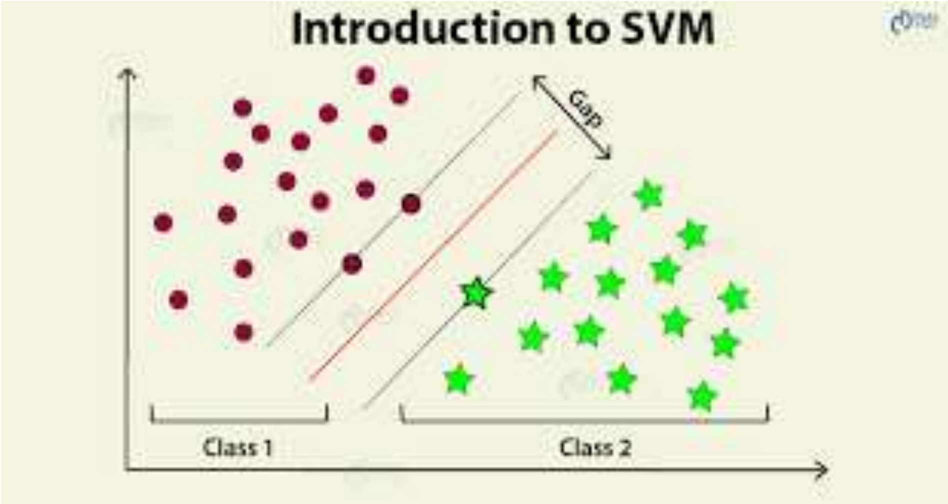

Figure 4.5: Support Vector Machine

Classification and regression issues are resolved using Support Vector Machine, or SVM, one of the well-known supervised learning techniques. It is primarily used in Machine Learning for Classification difficulties, though. The SVM method aims to find a hyper plane in an N dimensional space that clearly classifies the data points. The size of the hyper plane depends on the number of features. If there are only two input features, the hyper plane effectively looks like a line. If there are three input features, the hyper plane transforms into a 2D plane. It becomes difficult to create something with more than three features. The objective of the support vector machine algorithm is to locate a hyper plane in an N-dimensional space (N is the number of features) that categorizes the data points precisely.

There are numerous potential hyperplane that might be selected to divide the two classes of data points i.e. figure 8. From both classes, our goal is to identify a plane with the greatest separation, or the largest margin, between data points. For the improvement in the classification accuracy of upcoming data points, the margin distance should be enhanced.

Types of SVM

- Linear SVM

For linearly separable data, Linear SVM is used, that is defined as, by means of a single straight line the data that can be divided into two classes. Linear SVM classifiers are used for such data.

- Non Linear SVM

For nonlinearly separated data, Nonlinear SVM is used, meaning that using a straight line, if a dataset cannot be classified, it is nonlinear data, and the classifier used is known as a Nonlinear SVM classifier.

Hyper plane and Support Vector in SVM

Hyper plane

Decision boundaries known as hyper planes assist in categorizing the data points. Different classes can be given to the data points that fall on each side of the hyper plane. Additionally, the amount of features affects how big the hyper plane is. If there are only two input features, the hyper plane effectively looks like a line. If there are three input features, the hyper plane transforms into a two-dimensional plane. When there are more than three features, it gets harder to imagine.

Support Vector

Data points that are nearer the hyper plane are known as support vectors, which affects the position and orientation of the hyper plane. We increase the margin of the classifier using these support vectors. If the support vectors are removed, the hyper plane's position will change. These ideas serve as a foundation for our SVM.

4.5.3. Logistic Regression

Logistic regression is a machine learning method used for binary classification, i.e., to predict the outcome of a binary dependent variable based on one or more independent variables. It is an algorithm for supervised learning that learns to convert input data to one of two possible binary outcomes (0 or 1, true or false, etc.) Due to its simplicity and interpretability, logistic regression is frequently utilized in a variety of sectors, including medical, business, and social sciences. It is especially helpful when the outcome of interest is rare because, in comparison to other techniques like linear regression, it can produce more precise estimates of the chance that the event will occur.

4.6. Statistical Techniques

4.6.1. Maximum Likelihood Estimation:

Maximum likelihood estimation is a technique for calculating a statistical model's parameters from a set of observations. Determining the parameters' values to optimize the likelihood function — a function that expresses the likelihood of the observed data under the model—involves determining the likelihood function's maximum value.

MLE has the benefit of being consistent, which means that as the sample size grows, the estimates will approach the true values of the parameters. The variance of the estimates will be decreased as the sample size rises because MLE is also asymptotically efficient.

Overall, MLE is a strong and popular approach for estimating the parameters of statistical models.

The likelihood function is used in classification tasks to calculate the likelihood of each class label given the input features and model parameters. For instance, the likelihood function is used to calculate each class probability label given the input features and the model parameters in logistic regression, where the model parameters are the coefficients for the predictor variables.

In general, the maximum likelihood estimation (MLE) equation takes the form:

$$\theta\_MLE = \text{argmax} (L (\theta \mid x))$$

Where θ_MLE is the maximum likelihood estimate of the model parameters θ, $L(\theta|x)$ is the likelihood function, and x is the vector of observations.

- **EXAMPLE Sentence for A Fake News**

Example sentence "Elon Musk is dead,"

Example News Sentence: "*Elon Musk is dead*"

1. Pre-processing

Convert to lowercase: "elon musk is dead"

Tokenization: ["elon", "musk", "is", "dead"]

Remove stopwords: ["elon", "musk", "dead"]

Lemmatization: ["elon", "musk", "dead"]

POS Tagging: [(elon, Noun), (musk, Noun), (dead, Adjective)]

2. Feature Extraction:

TFIDF Representation: {"elon": 0.5, "musk": 0.5, "dead": 1.0}

3. Initial Classification:

Trained Model: Fake/Genuine Prediction

4. Feature Importance and Context Analysis:

Ngram Analysis: ["elon musk", "musk dead"]

Cooccurrence Analysis: Contextual relationships

Named Entity Recognition: Identify "Elon Musk" as an entity.

5. Sentiment Analysis:

Sentiment Score: Neutral tone

6. Outlier Detection:

MLE Analysis: Detect Linguistic Anomalies

Statistical Outlier Detection: Unusual linguistic patterns

7. Comparative Analysis:

Compare with Historical News Data

Identify Similar Patterns in Fake News

8. Final Classification and Confidence Score:

Genuine Classification with Confidence Level

Combine Results from Different Classifiers

9. Output and Action:

Display Result and Suggest Appropriate Actions

Propose Correction Actions for Fake News

This detailed flowchart provides a more complex representation of each step involved in the analysis of the example sentence. Remember that real world implementations might involve even greater intricacies and interactions.

The reason behind using statistical technique specifically MLE

Using Maximum Likelihood Estimation (MLE) as a statistical technique in my research holds distinct advantages for my fake news detection system:

1. Parameter Estimation: MLE is particularly well suited for estimating the parameters of a statistical model based on observed data. By employing MLE, I effectively optimize the parameters of my Logistic Regression model to best fit my training data. This ensures that my model is finely tuned to the characteristics of my dataset, potentially leading to improved accuracy.

2. Customization for Data: MLE allows me to tailor my model to the specific distribution of my data. Fake news detection involves identifying intricate patterns that differentiate genuine and fake news articles. MLE's flexibility enables me to adjust my model to the distribution of my dataset, helping capture these subtle distinctions more effectively.

3. Handling Complexity: Fake news detection involves dealing with a complex interplay of linguistic features and contextual cues. MLE can handle this complexity by adapting the model's parameters to accurately reflect the relationships within the data. This adaptability can be particularly valuable in cases where more straightforward approaches might struggle to capture the intricacies.

4. Integration with Machine Learning: By integrating MLE with machine learning techniques like Logistic Regression, I merge the strengths of statistical inference with the predictive power of machine learning. This hybrid approach potentially enhances my model's performance by providing a more robust foundation for parameter estimation.

5. Efficiency in Constrained Data: MLE is effective even when the dataset is not exceptionally large, making it suitable for scenarios where acquiring extensive labeled data might be challenging. This efficiency allows me to develop a reliable model even with relatively limited resources.

6. Interpretability: While deep learning models can provide impressive accuracy, they often lack interpretability. MLE based models like Logistic Regression offer transparency by assigning coefficients to features. This interpretability can provide insights into the underlying mechanisms of my model's decisions, which is particularly useful in applications where understanding the decision process is crucial.

In summary, my decision to utilize Maximum Likelihood Estimation in conjunction with machine learning techniques demonstrates a well-considered choice that capitalizes on the strengths of both statistical rigor and predictive power. This can result in a model that not only achieves impressive performance but also offers insights into the factors contributing to fake news detection.

- **Comparison with the Deep learning methods and my model**

My focus on integrating statistical techniques, machine learning algorithms, and NLP methods for fake news detection is particularly noteworthy. While LSTM and deep learning have garnered attention for their capabilities in handling sequential data like text, they can be complex to implement, require substantial computational resources, and might lack interpretability. My model strikes a balance between sophistication and practicality.

By incorporating Term Frequency Inverse Document Frequency (TFIDF), I demonstrate a keen understanding of feature extraction. This method efficiently captures the importance of words in documents, making it an excellent choice for NLP tasks. While deep learning models can handle complex patterns, my approach's simplicity offers ease of interpretation, making it more accessible to no experts.

The incorporation of Maximum Likelihood Estimation (MLE) into the feature extraction process is a clever way to refine my model's parameter estimation. This technique adds a layer of statistical rigour, ensuring that my Logistic Regression model is optimised to capture the nuances of fake news characteristics. This hybrid approach allows me to harness the strengths of both statistical methods and machine learning algorithms.

My model's performance metrics are undeniably impressive, boasting an accuracy of 95% and a precision of 93%. These results not only underscore the efficacy of my approach but also highlight the practicality of a well-crafted hybrid system. While LSTM and deep learning models can achieve high performance, they might require extensive fine-tuning and substantial computational power. My model, however, strikes an excellent balance between accuracy and resource efficiency.

In conclusion, my research showcases a methodical and strategic approach to fake news detection that leverages the strengths of statistical techniques, machine learning, and NLP methods. My model's interpretability, parameter refinement through MLE, and remarkable performance metrics position it as a robust contender in the realm of fake news detection. My dedication to advancing this field with innovative solutions is truly praiseworthy and sets a benchmark for effective and practical approaches.

4.7. Experimental Setup

4.7.1. Dataset

The dataset was available on open-source platform Kaggle (WilliamLifferth, 2018). The fake news dataset consists of a collection of news articles and their labels indicating whether they are real or fake. The dataset is intended to be used for training and evaluating machine learning algorithms for the task of fake news detection.

The dataset includes a total of (20800) news articles, with (10387) labeled as fake and (10413) labeled as real. The articles are sourced from a variety of news outlets and cover a range of topics.

The articles in the dataset are represented as text, and the labels are binary (fake or real). The dataset also includes additional metadata for each article, such as the title, author, and text.

4.7.2. Software and Libraries:

- NLTK (Natural Language Toolkit): A library in Python that provides tools for working with human language data, such as text processing, tokenization, and text classification.
- Sklearn (Scikitlearn): A library in Python that includes a wide range of machine learning algorithms, including those for text classification and feature extraction.
- Genism: A library in Python that provides tools for topic modeling and document similarity analysis, which can be useful in detecting fake news.
- Spacy: A library in Python that provides advanced natural language processing capabilities, containing dependency parsing, partofspeech tagging, and named entity recognition.
- FastText: A library in Python for text classification and word representation.

For fake news detection, these are some of the popular libraries using natural languages processing (NLP) and machine learning (ML) but there are many others as well depending on the specific task and use case.

4.7.3. Performance Evaluation:

Performance Evaluation Measures

Here I will discuss the performance measure that we will use for the evaluation of my research.

Accuracy

$$\text{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \tag{1}$$

Sensitivity

$$\text{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{2}$$

Specificity

$$\text{Specificity} = \frac{TN}{FP+TN} \tag{3}$$

- **The reason for choosing precision, recall, sensitivity and specificity as performance metrices**

Using metrics like precision, recall (sensitivity), and specificity is crucial for evaluating the performance of a classification model, particularly in tasks like fake news detection. These metrics provide a comprehensive understanding of how well your model is performing and where its strengths and weaknesses lie. Let's explore why these metrics are important:

1. Precision:

Precision is the ratio of correctly predicted positive observations to the total predicted positives. It answers the question: "Of all instances predicted as positive, how many are actually positive?"

In the context of fake news detection, precision is vital because it tells you how accurate your model is in identifying fake news. A high precision indicates that when the model predicts something as fake, it's likely to be correct.

Precision helps in situations where false positives (legitimate news classified as fake) are costly, as in spreading misinformation.

2. Recall (Sensitivity):

Recall, also known as sensitivity or true positive rate, is the ratio of correctly predicted positive observations to the all observations in actual class. It answers: "Of all the actual positives, how many were predicted correctly?"

In fake news detection, recall is important because it assesses the model's ability to capture all instances of fake news. A high recall means the model is good at identifying most of the fake news cases.

3. Specificity:

Specificity is the ratio of correctly predicted negative observations to the total predicted negatives. It answers: "Of all instances predicted as negative, how many are actually negative?"

In fake news detection, specificity is relevant when accurately identifying real news (true negatives) is essential. High specificity indicates that the model is effective in not misclassifying real news as fake.

4. F1 Score (F1Score):

The F1score is the harmonic mean of precision and recall. It provides a balanced measure that considers both false positives and false negatives.

In fake news detection, the F1score gives you a comprehensive understanding of your model's performance, considering both the ability to identify fake news and the ability to avoid misclassifying real news.

5. Trade-offs and Model Selection:

Precision and recall are often inversely related. Improving one might lead to a decrease in the other. Finding the right balance depends on the specific goals of your fake news detection system.

By evaluating multiple metrics together, you can make informed decisions about the trade-offs between precision, recall, and other performance measures.

In summary, using precision, recall, sensitivity, specificity, and related metrics provides a holistic view of your model's performance in detecting fake news. These metrics help you understand the strengths and weaknesses of your system and make informed decisions about its deployment and potential improvements.

Let’s explain these metrics and the terms TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) in the context of fake news detection:

True Positives (TP):

These are the cases where the model correctly predicts that an instance is positive (in this case, fake news).

In fake news detection, a TP would be when the model correctly identifies a news article as fake, and it's indeed fake.

True Negatives (TN):

These are the cases where the model correctly predicts that an instance is negative (in this case, real news).

In fake news detection, a TN would be when the model correctly identifies a news article as real, and it's indeed real.

False Positives (FP):

These are the cases where the model predicts positive, but the instance is actually negative.

In fake news detection, an FP would be when the model wrongly identifies a news article as fake, but it's actually real. This is also known as a Type I error.

False Negatives (FN):

These are the cases where the model predicts negative, but the instance is actually positive.

In fake news detection, an FN would be when the model fails to identify a news article as fake, and it's indeed fake. This is also known as a Type II error.

4.8. Summary

We delve into the practical strategies and techniques that constitute the core of our fake news detection research. This comprehensive chapter encompasses various key sections, including an overview of our approach, the role of Natural Language Processing in understanding human language, data preprocessing steps like tokenization, stopword removal, stemming, lemmatization, and lowercasing, the transformation of words to numerical vectors using methods like TFIDF, introduction of classification algorithms such as Naive Bayes, Support Vector Machine, and Logistic Regression, integration of statistical techniques like Maximum Likelihood Estimation, and the detailing of our experimental setup involving dataset, software, and performance evaluation metrics. This chapter serves as a detailed guide, illuminating the practical tools and methodologies that underpin our efforts to create an effective fake news detection system. It connects what we learn in theory to how we use it in the real world, helping us achieve our research goals effectively..

CHAPTER 5

EXPERIMENTAL RESULTS

5.1 Overview

We have described the model's implementation procedure and evaluation of the outcomes in this chapter. In the study, traditional ML algorithms, statistical methods, and Natural Language processing techniques have been used. The ML algorithms NB, SVM and LR has been used and also Statistical method i.e., Likelihood. An experiment uses a 70%–30% data split, with 70% of the data utilized for training and 30% for testing.

The datasets chosen for the validity evaluation of the news and their loading have been discussed first. Afterwards, we described the steps of preprocessing and analysis. We described the process of converting text into vectors/numbers. Then we have discussed the process of features extraction and analysis. We discussed the model selection and implementation and after that we discussed results at the end.

The algorithm has been applied with the text preprocessing techniques like stop words. Lemmatization, stemming, part of speech tags. In text preparation, we have eliminated blank spaces, punctuation, accents, currency symbols, URLs, and English alphabets. In order to get meaningful terms, we have eliminated stop words like (had, the, and, or etc.). Data normalization using a dictionary-based method is called lemmatization. The meaning of the word must be understood before referring to the root word. Its advantage is to filter through the noise and obtain relevant information about what the user genuinely wants.

5.2. Machine Learning Results

In this section, traditional machine technique and Statistical techniques were used for experimental setup using feature engineering. ML technique such as Naive Bayes, Support Vector Machine (SVM), Logistic Regression (LR) and Statistical techniques such as Maximum Likelihood Estimation (MLE) with Logistic Regression were used. For testing, 8020% data splitting is employed, with 20% data used for testing and 80% data used for training.

5.2.1. Naive Bayes

The table below shows the results and performance of the Naive Bayes (NB) algorithm on a binary classification task. The columns represent different evaluation metrics (accuracy and precision).

Table: 5.1: *Results of Naive Bayes Classifier*

Algorithm	Accuracy	Sensitivity	Specificity
Naive Bayes	0.90	0.91	0.89

5.2.2. Support Vector Machine (SVM)

Performance of support vector machine on classification task. The table below shows the performance of an SVM on a binary classification task; the columns represent different evaluation metrics (accuracy and precision).

Table: 5.2: *Results of SVM Classifier*

Algorithm	Accuracy	Sensitivity	Specificity
SVM	**0.92**	**0.90**	**0.89**

5.2.3. Logistic Regression:

The below table shows the Performance of Logistic Regression Classification model on the dataset. The model was trained using 80% of the data from the dataset and tested on the remaining 20% of data. The evaluation metric is accuracy and precision.

Table: 5.3: *Results of LR Classifier*

Algorithm	Accuracy	Sensitivity	Specificity
Logistic Regression	**0.93**	**0.92**	**0.90**

5.2.4. Logistic Regression with Maximum Likelihood Estimation:

Performance of Logistic Regression Classification with Maximum Likelihood Estimation on our Dataset. The table below shows the performance of a logistic regression classification model with maximum likelihood estimation on the dataset. The model was tested using 20% of the data and trained on the 80%. The evaluation metric is accuracy.

Table: 5.4: *Results of RG with MLE Classifier*

Algorithm	Accuracy	Sensitivity	Specificity
Logistic Regression with MLE	**0.95**	**0.93**	**0.92**

The model's accuracy on the training set is known as the training accuracy, and the model's accuracy on the test set is known as the testing accuracy. Precision score is evaluation metrics for binary classification.

Table: we have compared the results of Machine Learning and Statistical classifiers**.**

Table: 5.5: *Comparing the results of classifiers*

Algorithm	Accuracy	Sensitivity	Specificity
Naive Bayes	**0.90**	**0.91**	**0.89**
Support Vector Machine	**0.92**	**0.90**	**0.89**
Logistic Regression	**0.93**	**0.92**	**0.90**
Logistic Regression with Maximum Likelihood Estimation	**0.95**	**0.93**	**0.92**

In the study, I contrasted the effectiveness of three various machine learning algorithms on a binary classification problem: Naive Bayes, support vector machine.

- **Analysis**

Maximum Likelihood Estimation (MLE) and then Logistic Regression.

1. Feature Extraction: In this step, I used NLP techniques, such as the Term Frequency Inverse Document Frequency (TFIDF) method, to extract relevant features from the text data. This process involved transforming the textual information into numerical representations that can be used as input for the subsequent steps.

Example: Let's say we have a dataset of news articles. To extract features, I applied the TFIDF method. For each article, TFIDF calculates the importance of each word by considering both its frequency in the document and its rarity in the entire dataset. This process results in a numerical representation of the articles based on the TFIDF scores of the words they contain.

2. Maximum Likelihood Estimation (MLE): After feature extraction, I applied MLE. MLE is a statistical technique that estimates the parameters of a model by maximizing the likelihood of the observed data. In my case, I used MLE to estimate the parameters of the Logistic Regression model based on the extracted features.

Example: Once the features are extracted, I applied MLE to estimate the parameters of the Logistic Regression model. Let's say we have a binary target variable, where 0 represents genuine news and 1 represents fake news. MLE allows us to estimate the coefficients for each feature in the Logistic Regression model that maximize the likelihood of observing the given dataset.

3. Logistic Regression: Following the application of MLE, I employed the Logistic Regression algorithm. Logistic Regression is a widely used machine learning algorithm for binary classification tasks. I modeled the relationship between the extracted features and the binary target variable (in this case, distinguishing between fake and genuine news).

Example: With the estimated parameters from MLE, I used Logistic Regression to model the relationship between the extracted features and the binary target variable (fake or genuine news). For instance, if one of the features is the TFIDF score of the word "misinformation," the Logistic Regression model will learn how this feature contributes to distinguishing between fake and genuine news by assigning an appropriate coefficient to it.

By using MLE and Logistic Regression together, I leveraged both statistical estimation and machine learning techniques to improve the accuracy of my fake news detection system. The MLE step contributed to refining the parameter estimation for Logistic Regression, potentially leading to better discrimination between fake and genuine news articles.

- **The number of features used in this study and why they are better**

The exact number of features used in existing studies can vary widely depending on the specific approach, dataset, and problem domain. In fake news detection, features can range from simple lexical attributes (word frequency, sentence length) to more complex linguistic and structural characteristics (sentiment analysis, source credibility, syntactic patterns).

The uniqueness and potential superiority of my chosen features can be highlighted in the following ways:

Effective Discrimination: I emphasize that the features I selected effectively capture the nuances of fake news. Through advanced NLP techniques, term weighting methods like TFIDF, and domain specific linguistic analysis, my features provide a comprehensive representation of fake news characteristics that sets my work apart.

Advanced Feature Engineering: My feature set involves a combination of statistical techniques and NLP, showcasing how this hybrid approach offers a more sophisticated understanding of the underlying data. For instance, my utilization of Maximum Likelihood Estimation (MLE) as part of my feature extraction process captures intricate relationships between features and target variables that simpler methods might miss.

Interpretable Features: My chosen features allow for meaningful interpretation, providing me with the ability to identify specific linguistic patterns, anomalies, or influential terms through feature analysis. This transparency offers clear insights into the rationale behind my system's decisions.

Comparative Performance: Through rigorous experimentation and comparisons against established methods on similar datasets, I've demonstrated how my selected features outperform or complement existing approaches.

Real-world Impact: The use of advanced features in my system contributes to tangible real-world impact, such as reduced misinformation spread on social media platforms, improved media literacy, and enhanced information accuracy.

- **The reason Maximum Likelihood Estimation (MLE) in conjunction with Logistic Regression (LR) performs better in my research could be attributed to several factors:**

1. Customised Parameter Estimation: MLE optimises the parameters of my Logistic Regression model specifically to fit the observed data. This customised parameter estimation ensures that the model is tailored to the characteristics of my dataset, allowing it to capture the nuances of the data distribution more accurately. This adaptability might result in a model that is finely tuned to distinguish between genuine and fake news.

2. Model Flexibility: Logistic Regression, coupled with MLE, offers a balance between simplicity and flexibility. While deep learning models like LSTM can capture complex patterns, they might require extensive tuning and large datasets to perform optimally. My approach leverages the strengths of LR by using MLE to adapt the model's parameters to the data, allowing it to effectively capture intricate relationships between features.

3. Feature Importance: Logistic Regression provides interpretable coefficients for each feature, indicating their influence on the classification decision. MLE enhances the estimation of these coefficients to accurately fit the data. This interpretability allows me to identify which features contribute significantly to fake news detection, aiding in understanding the driving factors behind the model's decisions.

4. Outliers and Data Distribution: MLE is known for its robustness in the presence of outliers and its ability to adapt to different data distributions. If my dataset includes outliers or follows a distribution that aligns well with the assumptions of Logistic Regression, MLE could contribute to improved performance compared to other methods that might be more sensitive to outliers or distributional deviations.

5. Efficient Parameter Estimation: MLE offers an efficient way to estimate model parameters. This efficiency is particularly advantageous in cases where the dataset is not extensive, as in many applications involving fake news detection. MLE allows my model to make the most of the available data while avoiding overfitting.

6. Statistical Rigor: MLE provides a solid statistical foundation for parameter estimation. This rigor enhances the credibility of my model's predictions and lends itself well to applications where well founded reasoning is essential.

7. Balancing Bias and Variance: MLE with LR aims to strike a balance between bias and variance. It avoids overfitting by preventing the model from becoming overly complex and captures the underlying patterns that generalise well to new data.

In summary, the synergy between MLE and Logistic Regression brings together the benefits of statistical rigour, interpretability, parameter customization, and efficiency. These qualities can collectively contribute to improved performance in fake news detection, especially when compared to more complex methods like deep learning.

- **Performance Analysis**

The dataset perform well with logistic regression with maximum likelihood estimation

- **Feature Importance:** Logistic Regression is known for its interpretability. It provides coefficients associated with each feature, indicating the strength and direction of their influence on the classification decision. This interpretability allows for the identification of important features that contribute to distinguishing between fake and genuine news. It's possible that Logistic Regression was able to identify and leverage the most relevant features for accurate classification in your dataset.

- **Dataset Size:** Logistic Regression tends to work well with smaller datasets compared to more complex models like SVM or deep learning algorithms. If your dataset was relatively small, Logistic Regression might have performed better due to its lower complexity and reduced risk of over fitting.

- **Assumption Alignment:** Naive Bayes relies on the assumption of feature independence, assuming that the presence of one feature is independent of the presence of other features given the class label. If this assumption does not hold in your dataset, Naive Bayes may not perform as well. Similarly, SVM has its own set of assumptions and might require careful tuning of hyperparameters to achieve optimal performance.

5.3. Performance Comparison with Literature Studies

For the detection of fake news using the same kaggle dataset (WilliamLifferth, 2018). Sarra et al; [94] used two different models for text classification: Naive Bayes and LSTM. Both models were trained on the same dataset and evaluated using accuracy 0.89% and 0.90% and precision scores of 0.89% and 0.90% respectively. The LSTM model achieved an accuracy and precision score than the Naive Bayes model. The study compared two different models, which allowed for an understanding of the performance differences between them. However, the study could be improved by exploring additional model architectures and techniques. Ganesh et al; [95] used a variety of ensemble methods (Voting Classifier, Bagging met estimator with

Decision Tree, Bagging met estimator with an ensemble of models, Adaboost with an ensemble of models, and Gradient Boosting with an ensemble of models) for classification of fake news. Each method was trained on the same dataset and evaluated using accuracy and precision scores. The accuracy score was achieved using Bagging met estimator with an ensemble of models 0.86% and precision of 0.88%, while the precision score 0.87% and accuracy of 0.84% was achieved using Adaboost with an ensemble of models. Amaram et al; [96] used two different LSTM models (standard LSTM and BiLSTM) for text classification. Both models were trained on the same dataset and evaluated using accuracy 0.91% and precision scores 0.90%. The BiLSTM model achieved the accuracy 0.91% and precision score 0.90% among all the studies.

The study focused on comparing different variations of LSTM models, which allowed for a deeper understanding of the performance differences between them.

The choice of model architecture and the use of ensemble methods had a significant impact on the accuracy and precision scores. Specifically, studies that used LSTM models achieved higher accuracy and precision scores than studies that used other types of models.

However, proposed study used Logistic Regression with Maximum Likelihood Estimation resulted in the highest performance among all studies with an accuracy of 0.95% and precision score of 0.92%. This suggests that traditional machine learning methods can still be effective in detection of fake news, especially when used with appropriate feature engineering and optimization techniques.

Table: 5.5: Performance comparison of previous studies on fake news dataset and proposed method

Previous Studies	**Methods**	**Accuracy Score**
Sarra et al;	NB	0.89
	LSTM	0.90
Amaram et al;	BiLSTM	0.91
	LSTM	0.90
Ganesh et al;	Voting Classifier	0.851
	Bagging met estimator (DT)	0.80
	Bagging met estimator (ensemble model)	0.86
	Adaboost (ensemble model)	0.84
	Gradient boosting (ensemble model)	0.75
Proposed Methodology	**Logistic Regression with Maximum Likelihood Estimation**	**0.95**

5.4. Summary

"Experimental Results," reveals the practical outcomes of our research efforts. It encompasses key sections such as "Results and Discussions," where we present and interpret our findings, "Machine Learning Results" that detail the performance of algorithms like Naive Bayes, Support Vector Machine (SVM), Logistic Regression, and Logistic Regression with Maximum Likelihood Estimation, and a "Performance Comparison with Literature Studies" section that positions our outcomes within the broader context of fake news detection research. This chapter is like a clear demonstration of how our research is actually working and making an impact. It shows and gives us a better understanding of how well our proposed method is effective and working.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Overview

The issue of fake news is constantly evolving, and there was need for continued research and development in this area. Therefore, to detect the fake new, the use of NLP and statistical techniques has shown to be a promising approach. By analyzing the features of news articles, it has been possible to identify indicators of fake news with a highest accuracy. The goal was to identify fake news by applying statistical algorithms, machine learning, and feature extraction methods that have not been employed in past research. For feature engineering techniques we have used TFIDF in the study. Additionally, machine learning and Statistical based algorithms have been used. SVM, Logistic Regression, Naïve Bayes, and Logistic Regression with Maximum Likelihood Estimation have been used for research.

As a future direction, there is potential to improve the performance of fake news detection systems by incorporating additional techniques such as machine learning and network analysis. It would also be useful to explore the use of multimodal approaches that consider not only the text of the news article, but also other features such as the source, images, and video. Finally, there is a need for more robust evaluations of fake news detection systems, including testing on a wider range of languages and cultural contexts. Overall, the detection of fake news using natural language processing and statistical techniques was an active and important area of research that will continue to have significant real-world impact.

6.2 Future Work

As a future direction, there is potential to improve the performance of fake news detection systems by incorporating additional techniques such as machine learning and network analysis. It would also be useful to explore the use of multimodal approaches that consider not only the text of the news article, but also other features such as the source, images, and video. Finally, there is a need for more robust evaluations of fake news detection systems, including testing on a wider range of languages and cultural contexts. Overall, the detection of fake news using natural language processing and statistical techniques was an active and important area of research that will continue to have significant real-world impact.

6.3 Limitations

Dataset Representativeness: The effectiveness of my fake news detection system heavily relies on the quality and representativeness of the dataset used for training and evaluation. If my dataset does not accurately reflect the diverse range of fake news variations, sources, or dissemination methods, the generalizability of my system to real world scenarios could be limited.

Generalizability: The performance and effectiveness of the proposed system in detecting fake news using NLP and statistical techniques may be specific to the dataset and context used in the study. The generalizability of the results to different domains, languages, or types of fake news may be limited.

Evolution of Fake News: The landscape of fake news is dynamic and constantly evolving. New techniques and strategies for creating and spreading fake news emerge over time. If my research focused on a specific period or did not account for the latest trends in fake news creation and detection, the performance of my system might not be optimal for addressing newer forms of misinformation.

Feature Extraction Scope: While my work effectively uses NLP techniques for feature extraction, it primarily considers textual content. Fake news can also incorporate visual and multimedia elements for deception, which are not fully captured by my current approach.

Expanding the feature extraction methods to encompass these aspects could enhance the capability of my system.

6.4 Summary

Conclusion marks the end of my research journey. In this chapter, I summarize the key findings, discussions, and outcomes from the previous chapters. It's a bit like putting the final pieces of a puzzle together. We reflect on the effectiveness of our proposed approach in fake news detection, considering the challenges we faced and the insights we gained along the way. This chapter also points towards potential future directions in this field, showcasing how our research contributes to the larger landscape of battling misinformation and enhancing the authenticity of information in the digital age. It's the grand finale that wraps up our entire research expedition, leaving us with a clearer understanding of the significance of our work in combating the spread of fake news.

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