ANALYZING EFFECTS OF EMOTIONS ON FAKE NEWS DETECTION: A COVID-19 CASE STUDY

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ABSTRACT

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Keywords: Fake news detection, COVID-19 pandemic, Sentiment analysis, Emotion Extraction, Social Media, Lexicon, Machine Learning, Deep Learning

The rapid dissemination of fake news represents an important threat to the accuracy of the information, particularly in considering the COVID-19 pandemic. In this dissertation, the significance of detecting fake news has been studied, with particular attention paid to the impact that sentimental and emotional characteristics can have on the process of identifying it. On a COVID-19 Twitter dataset with labeled classes, the feelings and emotions of fake news against real news are compared. Lexicon-based sentiment analysis and emotion extractions methods are utilized for extracting the sentiments and emotions of the tweets. Three different sentiment lexicons are employed to generate the matching sentiment for each tweet, and the best performing lexicon is selected using a variety of techniques. Vader sentiment lexicon provides the most effective results. According to the sentiments displayed by Vader, fake news involve larger quantity of negative emotions than positive emotions. The tweets are evaluated with the NRC emotion lexicon, which allows for the extraction of eight basic emotions, including anticipation, anger, joy, sadness, surprise, fear, trust, and disgust. It has been discovered that negative feelings like fear, anger, and disgust are more prevalent in fake news than they are in real news. These emotions are also expressed, in a more powerful manner, via fake news. On the other hand, feelings such as trust, joy, and anticipation are more prevalent in real news, both in terms of the amount of such feelings and the intensity with which they are expressed. According to the findings, feelings have the potential to play an important role as elements in the development of fake news identification models.

The SVM, Naive Bayes, Random Forest machine learning, and BERT deep learning models are implemented in order to validate this hypothesis. Comparisons are made between the performance of the models with and without the inclusion of emotional details. The findings show that incorporating emotional aspects into fake news detection models improves the performance of the detection model. This dissertation introduces novel features and approaches that contribute to the advancement of the field of detecting fake news. The findings highlight the significant emotional and sentimental differences among fake and real news on the COVID-19 twitter data set and highlight the important role that emotions play in the detection of fake news and provide useful insights into the process of training fake news detection models to recognize and make efficient use of these features.

ÖZET

DUYGULARIN SAHTE HABER TESPİTİ ÜZERİNDEKİ ETKİLERİNİN ANALİZİ: BIR COVID-19 VAKA ÇALIŞMASI

BAHAREH FARHOUDINIA

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Anahtar Kelimeler: Sahte haber tespiti, KOVID-19 pandemisi, sözlük, Duygu analizi, Duygu çıkarımı, Makine öğrenimi, Derin öğrenme

Sahte haberlerin hızla yayılması, özellikle Kovid-19 pandemisi sürecinde bilginin güvenilirliğini tehdit etmektedir. Bu doktora tezi, sahte haberleri tespit etmenin önemini, haberlerde uyandırılan duygusal ve bilişsel faktörlerin rolleriyle birlikte ele almaktadır. Ayrıca, sahte haberlerin yayılmasına katkıda bulunan bireysel davranışları da incelemektedir. Kovid-19 temalı Twitter veri kümesindeki gerçek ve sahte haberlerin duygu etiketleri sınıflandırılmış ve sözcük ve sözlüklere dayalı duygu analizi ve çıkarım teknikleriyle uyandırılan duygular belirlenmiştir. Her bir tweet için uygun duyguyu seçmek üzere üç farklı duygu sözlüğü test edilmiş ve en etkili olanı uygulanmıştır. Test edilen sözlüklerden Vader duygu sözlüğü en iyi sonuçları vermiştir. Sahte haberlerin olumsuz duygularla, gerçek haberlerin ise olumlu duygularla ilişkili olduğu görülmüştür. Tweetleri daha detaylı analiz etmek için sekiz temel duygu (beklenti, öfke, neşe, özlem, şaşkınlık, korku, güven ve tiksinti) içeren NRC duygu sözlüğü kullanılmıştır. Bulgular, olumsuz duyguların (korku, öfke, iğrenme) sahte haberlerde daha sık ve daha güçlü bir şekilde ifade edildiğini; olumlu duyguların (güven, neşe, beklenti) ise gerçek haberlerde hem sayıca hem de yoğunlukça daha fazla olduğunu ortaya koymuştur. Araştırma sonuçları, duyguların sahte haber tespit modellerinin geliştirilmesinde önemli bir rol oynayabileceğini göstermektedir. Haberlerin paylaşıldığı tweet metinlerinin uyandırdığı duygulara göre sahte ve gerçek haberleri ayırt etmek için SVM, Naive Bayes, Random Forest makine öğrenmesi ve BERT derin öğrenme modelleri kullanılmıştır. Bu bağlamda, modellere duygusal detayların dahil edilip edilmediği durumlarının performansları karşılaştırılmıştır. Sonuçlar, sahte haberleri tespit etmek için modellere duygusal unsurların eklenmesinin performansı iyileştirdiğini göstermiştir. Bu doktora tezi,

sahte haberlerin belirlenmesine yönelik araştırmalara katkı sağlamaktadır.

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1. INTRODUCTION

The potential for misleading information spread on social media to lead to significant challenges for society makes it imperative that this phenomenon be thoroughly investigated. Accessibility, cheap prices, and convenience of use in terms of information sharing make social networks like Facebook, Twitter, and Instagram popular sources of information among users. These factors contribute to the popularity of these social networks as information sources. The way people live their lives has been substantially disrupted by social media. For example, social networks make it simple to rekindle relationships with long-lost contacts and to get to know new individuals who have similar passions and ways of life. The spread of false information through social media platforms can have serious consequences for society. Because fake news is able to disseminate swiftly across a variety of platforms and reach a large audience, it has the potential to affect the results of political elections and to undermine individuals' faith in established organizations (Kumar, Bezawada, Rishika, Janakiraman & Kannan, 2016).As an illustration, the dissemination of fake news can have an effect on democratic procedures and serve as an instrument in propaganda efforts. During the presidential vote that took place in the United States in 2016, pieces from fake news sites had far more engagement than those from highly recognized news publications such as the New York Times (Silverman, 2016). Fake news can have an impact on people's decisions in various circumstances. In delicate situations, such as those involving health issues, this can be dangerous. A rumor circulated during the COVID-19 epidemic that "5G harms the human immune system". Numerous people set fire to the 5G towers in Europe after believing this report (Mourad, Srour, Harmanai, Jenainati & Arafeh, 2020). According to the "World Health Organization (WHO)", The spread of false information and propaganda was much quicker than the epidemic caused by COVID-19, which therefore led to mental distress, misinformation among medical professionals, and economic crisis (Mourad et al., 2020).

As a result of advancements in digital technology and social media platforms, it is becoming increasingly difficult to identify fake news on social media. It is imperative that research be conducted on the features of fake news, and that mechanisms for automatically identifying fake news be developed, if we are to prevent the potential damage that might be caused by fake news. It is very necessary for technology firms, researchers, educators, and government agencies to work together in order to create effective measures to combat the dissemination of fake news.

1.1 Key Research Challenges

In spite of the fact that research on fake news has attracted a lot of interest, there is still a need for more study in this sector. On social media or other channels, modern technology such as Artificial Intelligence (AI) that includes Natural Language Processing (NLP) may be used to detect and identify fake news; yet, same tools can also manufacture fake news on their own. It is vital to examine the features of fake news and develop detecting systems that are both efficient and accurate in order to stop its spread. Fake news is a multidisciplinary field of study, and research gaps in different disciplines and research areas are stated below:

- Fake news detection
  There has been a lot of study and work done to identify fake news, but there is still a need for more accurate models and tools that anybody can use to identify fake news. These models and tools should be accessible to the general public. These algorithms and technologies need to be able to distinguish between real news and fake news. It is almost certain that labeled data sets that have been categorized by humans will be of assistance in the process of enhancing the detection models. Additional research might be done to investigate the significance of the importance and effect of linguistic and semantic elements, feelings, emotions, and transmission patterns in identifying fake news. Methods of sentiment analysis can be applied to the study of the feelings that are elicited by fake news in order to gain a greater understanding of the linguistic and emotional features of this phenomenon (Farhoudinia, Ozturkcan & Kasap, 2022). Unsupervised machine learning, deep learning, and transfer learning can be utilized to design better detection models. The big data available in social media can be efficiently used with these methods to improve detection models to provide real-time and accurate fake news detection models.

- Fake news during the crisis
  The COVID-19 pandemic is an instance that demonstrates how, despite the advancement of science and the application of contemporary technology, people are still unaccustomed to crisis situations and might react irrationally. In these difficult times, fake news can spread more widely and be more deadly than at other times. In order to effectively combat fake news in similar situations in the future, during a time of such widespread epidemic or crisis, it is critical to have a solid understanding of the distinguishing characteristics of fake news. The more comprehensive academic research conducted on this subject, the better resources will be available in the future to develop strategies and road maps.

- Conspiracy theories
  Conspiracy theories are a complex area of research. It's still unclear how false news and conspiracy theories are related to one another and how they affect one another. Researchers should investigate how conspiracy theories interact with and influence the spread of fake news, and explore strategies to counteract their combined effects.

- Psychological and cognitive studies
  The reasons, motives, and cognitive features that correspond confidence to believing fake news are some of the themes that may be explored in future study. Other topics that can be examined include cognitive biases that influence their perception as well as the psychological impacts of being exposed to fake news. Data analysts and psychologists should work together on subjects that integrate human-based and internet data since there is a demand for this type of collaboration. This partnership has the potential to give an in-depth knowledge of fake news, including how it is created and disseminated as well as the consequences of its consumption.

- Cross-cultural and cross-national studies
  Fake news in different countries and cultures could have different features and effects on society. Fake news features and the sharing behavior of individuals interacting with it can be an interesting subject to study.

- Management and marketing
  Management strategies must be defined that can be employed by companies to identify and reduce the impact of fake news on their brand or company

and explore the best ways to manage such situations. Further research can provide guidelines on the most effective response strategies for companies using historical data or by performing experimental studies.

- Ethical and legal issues
  Freedom of speech and the responsibility of online platforms for fake news spread are examples of ethical challenges related to fake news. Currently, there is a lack of sufficient policies concerning appropriate behavior and interactions with websites and individuals that disseminate false information. The balance between protecting against fake news and preserving freedom of speech is a controversial topic that requires great attention from academia.

1.2 Research Purpose

The purpose of this research is to examine the phenomenon of fake news and to place particular emphasis on the ways in which feelings and emotions play an important role in distinguishing fake news from real news. People regularly utilize their feelings to convey how they feel about a subject, a person, a company, or any notion through the posts that they share on social media. These posts can be about anything. These emotions could be good or they might be negative. The publishers of fake news have two primary objectives: to attract the greatest possible audience and to get the highest possible number of shares. They resort to a variety of strategies in order to make the information they provide interesting to consumers. Emotions are elements that can help them market their key goal and enhance the exposure of their postings on social media, both of which are important for reaching their primary target audience. The application of features is the means through which this can be performed. People are able to immediately recognize the emotions that are sent by texts; nevertheless, it may not be as simple for them to realize the concealed intent that is being communicated by the words. Emotions have the ability to function as early indications as to whether or not an article includes actual information. The findings of this dissertation may be applied in two ways: first, they can be used to educate the general public about the dangers of consuming this kind of material on social media; second, they can be used to include these characteristics into algorithms that automatically detect fake news. Additionally, doing study on the emotions provoked by false information during global crises such as COVID-19 can give vital insight into the emotions that individuals are experiencing in these types of circumstances as well as the sort of information that they are willing to trust and share with others. In conclusion, the purpose of this research is to cover two research topics that require more study by incorporating features to enhance the fake news detection models and by analyzing false news during the crisis on social media during the crisis. In other words, the goal of this research is to provide a comprehensive overview of both of these research fields. In this particular incident, measures are being taken to combat the COVID-19 pandemic.

1.3 Study Design and Methodology

In order to guarantee the quality of the research conducted for this study, a complete research method was utilized. This was done with the intention of investigating and determining the emotional aspects of fake news in the most time-effective manner possible. For the purpose of this investigation, it is essential to make certain that the data set that is being investigated originates from a reliable source and that it is a well-rounded collection of information that includes both fake news and real news in quantities that are enough and proportionate to one another. There is an emphasis placed on ensuring the dependability and authenticity of the data, including steps such as the manual verification of labeled samples. Lexicographies that are efficient in managing the unstructured textual material that is present in social media are being used in this study so that the objectives of the research may be met. The purpose of the study is to determine the traits that distinguish true news from fake news that is spread via social media in order to provide a basis for future research. It is vital to carry out the appropriate pre-processing operations and significance test methods in order to ascertain the efficacy of the models and take into account any potential limits. Moreover, it is important to note that these procedures are carried out in order. As evaluation tools, we make use of the efficacy of the detection model as well as reliable evaluation metrics such as accuracy, recall, and F1-score.
This study emphasizes the significance of fake news and describes the substantial effects it has on societies, businesses, and people. The following research questions are intended to be addressed by this study: 1. How do the sentiments associated with real news and fake news differ? 2. How do the emotions of fake news differ from fake news? 3. What particular emotions are most prevalent in fake news? 4.

How could these feelings be used to recognize fake news on social media? This study was designed to test the idea that true news and fake news are distinct, particularly with regard to the emotions they elicit. The hypotheses suggest that true news has a greater proportion of positive stories than does fake news. In addition, fake news frequently emphasizes powerful, negative emotions such as rage and terror, whereas true news is presented in a composed and level-headed manner. This study addresses the problem by putting an emphasis on feelings as an important distinguishing factor. A comparison of the frequency and strength of the most common feelings evoked by fake news with those evoked by real news is presented.
The data set for this study includes Twitter data that were collected by filtering hashtags relating to COVID-19. This data set has been classified as true and fake by humans after examining trustworthy news sources. In addition to suggesting a new important component for fake news detection models, the findings of this study provide information about how people felt and expressed their emotions during the COVID-19 pandemic. The techniques used in this work include emotion extraction using emotion lexicons and sentiment analysis using various sentiment lexicons. Every tweet is given an emotion score based on the emotion lexicon employed in this study. The emotion with the highest score determines what the tweet's main emotion is. Additionally, comparing the scores would allow one to assess the intensity of these feelings. The findings provide light on the sentimental and emotional characteristics of false news in comparison to actual news and give significant insights about such characteristics.

1.4 Contribution and Conclusion

A sentiment analysis performed on the COVID-19 fake news data set reveals that the number of tweets containing negative emotions is larger than the number of tweets containing positive sentiments in fake news, and the feelings that are conveyed in fake news are more negative than those that are expressed in true news. By using the NRC emotion lexicon for every tweet in the data set, eight scores for eight emotions are assigned (Mohammad 2013a). These emotions are anger, anticipation, disgust, fear, joy, surprise, sadness, and trust. The emotion with the highest score is assigned to every tweet. According to the findings, people are more likely to feel fear, anger, and disgust after reading false news rather than after reading true news. Real news, on the other hand, is far more likely than false news to elicit favorable feelings such

as trust, surprise, anticipation, and joy. This validates the study's initial hypothesis that there are differences in the sentiments and emotions evoked by real news and fake news, with fake news evoking more negative and intense reactions than real news. The intensity of the feelings is examined by comparing the emotion scores offered by the lexicon. The results show that fake news expresses negative emotions like fear, anger, and disgust more powerfully than real news. The results of the statistical test indicate that there is an important distinction between the emotions evoked by fake news and those elicited by real news, particularly with regard to sentiments of anticipation, anger, disgust, fear, and surprise. The effectiveness of these feelings is evaluated in a variety of models for detecting fake news by utilizing machine learning and deep learning techniques. The performance metrics of the detection models demonstrate that emotion characteristics have a good influence on the accuracy of the models that are applied.
This study is to investigate the significant role that feelings play in the process of recognizing the characteristics of fake news on social media. In the past, researchers have not paid much attention to the feelings elicited by fake news or the ways in which these feelings contrast with those elicited by true news. This study contributes to the field by introducing crucial and significant characteristics of fake news and by addressing the beneficial effect of these features in detecting fake news. This study also addresses the positive impact of these characteristics in identifying fake news. The data collection on which this study is based contains both fake and real news articles relating to the COVID-19 epidemic. It is anticipated to discover such trends in other connected areas of study as well.

1.5 Outline

In chapter 2, a detailed assessment of the published research is presented. The research from a number of fields, such as management, psychology, and computer science. The analysis of sentiment and the extraction of emotions are the primary focuses of Chapter 3. It includes the methods and the findings for the purpose of emotion extraction as well as the objective of sentiment analysis. The techniques and outcomes for detecting fake news are discussed in Chapter 4, while Chapter 5 includes the discussion, research implications, limitations, and recommendations for future research. The investigation is brought to a close in the fifth chapter, which provides a summary of both the procedures and the findings.

2. LITERATURE REVIEW

In this chapter, a literature review on the subject of fake news is presented. The literature review encompasses a wide range of fields, including management, psychology, and computer science, among others. This chapter is organized as an introduction, definition of fake news, fake news in health, fake news from a psychological perspective, fake news in business and management, and fake news in computer science. A conclusion summarizes the findings.

2.1 Introduction

The widespread spread of misinformation has become a significant issue, particularly in the field of healthcare, due to its quick dissemination. The ease of accessing information on social media platforms enables the rapid spread of misinformation, resulting in significant consequences. The extraordinary growth of fake news is threatening democracy, justice, freedom of expression, and public trust, further intensifying the need for more research on this topic. In order to achieve the successful implementation of democracy in a society, the people in that society and the society itself need to be well-informed and possess accurate information. The proliferation of misleading information makes it more challenging for people to gain access to material that is accurate and make the best decisions. The public's perception of legal cases can be skewed by misleading information, which can then lead to biases. The concept of free expression is susceptible to being exploited by those who produce false news. Miró-Llinares & Aguerri (2023), Also, the rise of fake news stories might make it more challenging for individuals to differentiate between credible sources of information and to put their faith in legitimate news organizations (Allcott & Gentzkow, 2017). In 2019, there has been a significant increase in the amount of research conducted on fake news. Figure 2.1 illustrates the frequency of articles published in the Chartered Association of Business Schools (ABS) with respect to their publication years, ranging from 2010 to 2020.

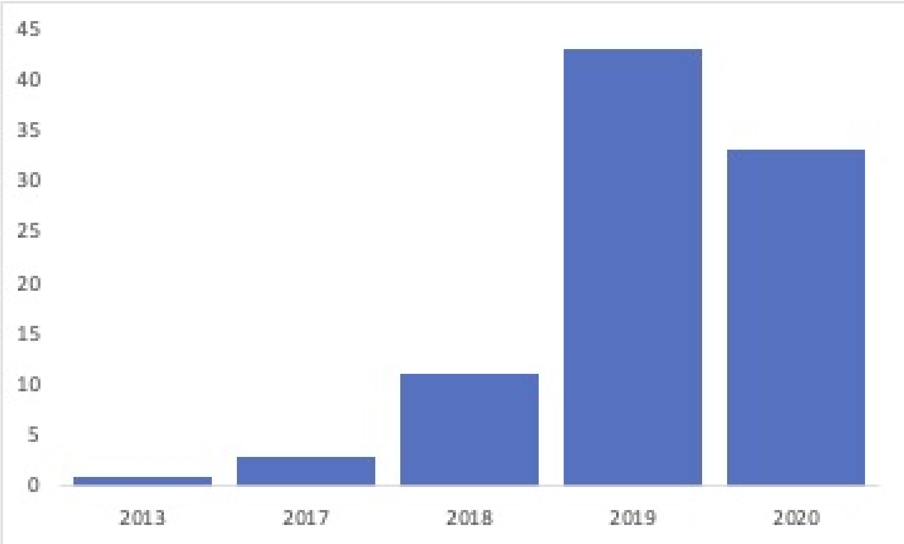

Figure 2.1 Frequency of published articles in ABS journal list 2010-2020 (author's own representation)

The presidential election that took place in the United States in 2016 is a good point of departure for research in this area (Carlson, 2020; Silverman, 2016; Wang, McKee, Torbica & Stuckler, 2019). In the 2016 American presidential election, Facebook-based fake news sources were believed to have a significant impact on the results of the election (Meel & Vishwakarma, 2019).
Fake news is a multidisciplinary field of study and the literature involves research papers in different disciplines such as articles in each field, including journalism, health, psychology, political science, information science, computer science, management, and marketing.

The COVID-19 pandemic has only heightened concerns about fake news. The spread of fake news during the pandemic, such as linking 5G cell towers to human immune system issues, lead to serious and dangerous consequences (Mourad et al., 2020). Many researchers focus on fake news, with a particular focus on the COVID-19 pandemic (e.g., Elías & Catalan-Matamoros, 2020; Hartley & Vu, 2020; Islam, Laato, Talukder & Sutinen, 2020; Laato, Islam, Islam & Whelan, 2020; Marin, 2020; Naeem & Bhatti, 2020; Pennycook, McPhetres, Zhang, Lu & Rand, 2020; Rand, Pennycook, McPhetres & Zhang, 2020). Thelwall & Thelwall (2020) introduce Twitter as a factor affecting information sharing during the COVID-19 pandemic, and it was also widely used to spread fake news. Vosoughi, Roy & Aral (2018) argue that the dissemination of false narratives on Twitter occurs at a more rapid pace compared to the propagation of factual tales. This phenomenon poses a significant vulnerability for firms and organizations, as they become susceptible to the adverse repercussions associated with the proliferation of misinformation. The dissemination of false information about a firm has the potential to exert an impact on the stock price of the company, hence resulting in significant financial ramifications.

2.2 Definitions of Fake News

The definition of fake news based on Oxford Advanced leaning dictionary is "false reports of events, written and read on websites", however, there are many definitions of "fake news" that may be found in published articles. a frequently referenced definition is presented by Allcott & Gentzkow (2017). They define fake news as *"news articles that are intentionally false, and could mislead readers."* Chen & Cheng (2020) introduce the terms disinformation and misinformation. They define disinformation as *"false or inaccurate information that is intentionally spread to deceive or manipulate."* In contrast, they define misinformation as *"false or inaccurate information that has been spread unintentionally."* This definition is also widely used by researchers. A more general definition is provided by Ozbay & Alatas (2020) as any low-quality or incomplete news. Table 2.1 introduce examples of research articles for every definition.

The general definition of any kind of false information that is spread in social media is followed by this study (Ozbay & Alatas, 2020); however, the findings of the research can give insights about the intention of the fake news. Fake news involves the dissemination of fabricated or distorted content through various media platforms, including traditional media, social media, websites, or online forums. The creation of fake pictures and movies is now possible because of recent developments in computer graphics, computer vision, and machine learning.(Agarwal, Farid, El-Gaaly & Lim, 2020). The term "deep fake" specifically refers to highly convincing digital content, particularly in the form of videos, which can pose a significant threat to politicians, celebrities, companies, and brands. Additionally, clickbait, an often-seen type of misinformation that is widely disseminated on social media platforms is the use of attention-grabbing headlines to lure people into clicking on links that direct them to different web pages, typically offering only incomplete or partial information (Chua, Pal & Banerjee, 2021).

Table 2.1 Example articles for different definitions of fake news

Definition	Article
Misinformation	Berthon & Pitt (2018)
	Acker & Donovan (2019)
	Carrieri et al. (2019)
	Brashier & Schacter (2020)
	Islam et al. (2020)
Disinformation	Karlova & Fisher (2013)
	Dawson & Innes (2019)
	Xia et al. (2019)
	Innes (2020)
Both definitions	Allcott & Gentzkow (2017)
	Chen & Cheng (2020)
	Colliander (2019)
	Flostrand et al. (2020)
	Kim & Dennis (2019)
	Kim et al. (2019)
	Lee et al. (2019)
	Borges-Tiago et al. (2020)
	Di Domenico & Visentin (2020)
	Kwanda & Lin (2020)

2.3 Fake News in Health

There is a significant concern with fake news in the field of health, with misleading information circulating extensively and having the ability to influence the decisions and actions of individuals towards their own health Abd Elaziz, Dahou, Orabi, Alshathri, Soliman & Ewees (2023). Fake news in health can originate from various sources, such as social media platforms, low-credibility websites, and individuals sharing misinformation unintentionally. Lewandowsky, Ecker & Cook (2017) suggest sensational headlines, exaggerated claims, and lack of scientific evidence as characteristics of fake news. Fake news in the health sector frequently concerns controversial subjects like vaccines, alternative therapies, and nutrition, and it does so by emphasizing on the fears and uncertainties of its readers. A crucial consequence that can result in major crises is the spread of fake news that is connected to health. This can cause individuals to make incorrect decisions regarding their health, such as shunning treatments that are not supported by evidence or engaging in behaviors that could be detrimental.(Brennen, Simon, Howard & Nielsen, 2020). Fake news can increase vaccine hesitation, healthcare professional distrust, and public health hazards (Lewandowsky et al., 2017). Wang et al. (2019) undertake a study of the literature on false information about health spread via social media, analyzing 40 research papers published between 2010 and 2020. They list many forms of misleading information about health, such as assertions about the effectiveness of treatments, disease origins, and conspiracy theories. It also explored how the spread of health-related fake stories might have an adverse effect on public health, including its role in promoting vaccine hesitancy, encouraging risky health behaviors, and undermining trust in public health authorities.

Melchior & Oliveira (2022) the main causes of the propagation of fake news concerning health on social media platforms, as well as the methods employed to stop it, such as fact-checking, social media platform policies, and public health campaigns. Balakrishnan, Zhen, Chong, Han & Lee (2022) conduct a review specifically focusing on the infodemic and fake news related to COVID-19. They examine 74 research papers published between 2020 and 2021, exploring false claims about the virus's origins, conspiracy theories, and inaccurate information regarding vaccine effectiveness and treatments. The authors highlight research gaps, such as a shortage of research on the effects of the infodemic on public health and healthcare systems, as well as insufficient studies on the efficacy of measures taken to stop the spread of false information. In addition, the authors point out that research on the effects of the infodemic on public health and healthcare systems is lacking. Ahmad, Aliaga Lazarte & Mirjalili (2022) study the part fake news played in the COVID-19 outbreak and how AI was used to stop it. They review 56 research papers published between January and December 2020. The authors identify limitations in existing approaches, such as the need for more accurate and efficient NLP techniques, improved training data, and addressing potential biases and errors in AI-based systems. They recommend future interdisciplinary research combining approaches from computer science, communication studies, and social sciences. To combat health-related fake news, clear and accessible health messaging from trusted sources that provide accurate information to the public can play a significant role. Additionally, effective communication between professionals and patients to address their concerns contribute to combating fake news in health (Kata, 2010).

2.4 Fake News from Psychological Perspective

Several research has been carried out in an effort to find an answer to the topic of why individuals believe and spread false information. Al-Rawi, Groshek & Zhang

(2019); Apuke & Omar (2021a); Talwar, Dhir, Singh, Virk & Salo (2020) investigate the motivations and psychological factors to accept and share fake news. Researchers hope to uncover the underlying mechanisms behind the spread of fake news. One important aspect in combating fake news is identifying the characteristics of those who actively contribute to fake news shared on social media. Sela, Milo, Kagan & Ben-Gal (2019) study the psychological profiles of individuals prone to sharing fake news, focusing on the motivations and cognitive biases that drive their behavior. Chen & Cheng (2020) examine the social factors and network structures that contribute to the spread of fake news. Brashier & Schacter (2020) study the cognitive mechanisms in the acceptance and propagation of fake news. They investigate how factors like memory distortions can affect an individual's susceptibility to fake news. Additionally, Duffy, Tandoc & Ling (2020) explore the role of emotion in the spread of fake news. They examine how emotional responses and social sharing behavior interact to shape the viral nature of fake news. Confirmation bias is one of the most important aspects that play a role in the dissemination of false news. This refers to the tendency of individuals to favor information that is consistent with the ideas they have already had in the past(Kim & Dennis, 2019). Cognitive bias often causes people to share and believe the contents that confirm their worldview without reliable evidence. As a result, fake news that is aligned with people's biases can easily spread through social networks. In the realm of decision-making, Kahneman (2011) introduce a dual process theory. This theory suggests that there are two distinct modes of thinking for humans: system 1 and system 2. System 1 thinking is intuitive, fast, and prone to biases, including confirmation bias. On the other hand, System 2 thinking is reflective, deliberate, and requires more cognitive effort. Moravec, Kim & Dennis (2020) suggest that social media evoke system 1 cognition from users, because of its fast-paced nature. Therefore, users may share misleading information without evaluating its veracity. Social media platforms with their special algorithms that deliver personalized content can inadvertently foster echo chambers. Therefore, individuals are surrounded by like-minded people and are far from exposure to diverse perspectives (Meel & Vishwakarma, 2019). Allcott & Gentzkow (2017) study the role of social media in the spread of misinformation. They highlight the significant effect of personalized content delivery in creating echo chambers. Berthon & Pitt (2018) focus on the effect of echo chambers on political polarization. Chua & Banerjee (2018) investigate the psychological mechanisms behind echo chambers. They study how cognitive bias contributes to the formation of these isolated information environments. Peterson (2019) focus on the role of echo chambers in fostering radicalization and extremist ideologies. They disclose that closed information networks can contribute to the spread of dangerous beliefs. Di Domenico & Visentin (2020) focus on the consequences of distorted information flow on democratic processes. Consequently, false information spread in social networks reinforces their impact on public understanding of important issues. Conspiracy theory is a belief that is created by a group of people to mislead people to achieve their own goals (Douglas, Sutton & Cichocka, 2019; Goertzel, 1994). It involves the idea that powerful groups are manipulating events and going against what most people believe to be true. The production, diffusion, and acceptance of false news, as well as the consequences of these phenomena on individuals' beliefs and actions, can all be assisted and encouraged by conspiracy theories. In human history, conspiracy theories are presently driven by the human desire to explain complex events (Goertzel, 1994). Conspiracy theories have certain characteristics. These characteristics include a general skepticism towards official explanations or narratives provided by authorities. The assumption that there are hidden intentions underlying events or acts is typically promoted by conspiracy theories, which imply that influential groups or people are influencing events for their own gain. Additionally, conspiracy theories often rely on unproven or unscientific evidence, rather than solid facts, to support their claims (Douglas et al., 2019; Sunstein & Vermeule, 2009). The generation and dissemination of erroneous information can sometimes be fueled by conspiracy theories. Within societies that subscribe to conspiracy theories, the circulation of false news may bolster preexisting ideas, create echo chambers, and deepen suspicion in the media (Pennycook, Cannon & Rand, 2018). Furthermore, conspiracy theories can give credibility to fake news by supporting the misinformation (van Prooijen, Krouwel & Pollet, 2018). The proliferation of false news among groups that are dedicated to conspiracy theories erodes public faith in reputable sources, lowers the level of discourse and debate that takes place within democratic societies and adds to the polarization of those living in those societies. (Swami, Voracek, Stieger, Tran & Furnham, 2014). Uscinski & Parent (2014) suggest that It is possible to lessen the impact of conspiracy theories and false news by encouraging open discussion, openness, and trust within the mainstream media. In most cases, the interplay between false news and conspiracy theories results in a significant problem for civilizations. Individuals and society as a whole may be negatively impacted when conspiracy theories and false news are disseminated; hence, it is vital to have an understanding of the psychological and social repercussions of these phenomena in order to develop effective countermeasures to counteract their influence O'Hair & O'Hair (2020). By fostering media literacy, critical thinking, and programs aimed at establishing trust, It is possible to curb the circulation of false information and foster the growth of a society that is better informed. Experiments and surveys have been carried out by psychological researchers in this sector in order to gain a deeper understanding of the user's behavior and motives in relation to fake news. Lutzke, Drummond, Slovic & Árvai (2019) focus on Facebook's role in spreading misleading information about climate change. They study the effectiveness of interventions to promote critical thinking among Facebook users. They provide users with two interventions, the first provides users with a brief pre-exposure warning message and the second stimulates people's critical thinking regarding the factors that led to the production of fake news by encouraging them to consider them. The researchers measured participants' attitudes before and after exposure to fake news and interventions. They find that interventions have a positive effect on reducing the influence of fake news on individuals. Those individuals who were exposed to the interventions had a lower likelihood of believing that fake news was true, particularly when it related to critical topics such as climate change. Wolverton & Stevens (2019) study the role of personality traits in individuals' ability to recognize disinformation. They claim that understanding the role of personality in recognizing disinformation can be helpful for the development of strategies to combat fake news spread. They conduct an online survey in which participants are presented with news articles, they are asked to evaluate the credibility of news. Participants also complete personality trait assessments to measure personality dimensions such as openness, honesty, agreeableness, and neuroticism. They suggest that participants who are high in openness can exhibit better skills in identifying disinformation, however, those high in agreeableness are found to be more susceptible to false information. They highlight the importance of individual differences when designing strategies to combat disinformation. According to Talwar, Dhir, Kaur, Zafar & Alrasheedy (2019) factors such as online trust, self-disclosure, fear of missing out (FoMO), and social media fatigue are positively related to sharing behavior. Their study involves conducting a survey with Indian WhatsApp users as their sample population. In another study by Laato et al. (2020) it is found that trust in online information is a strong predictor of sharing unverified information.They conduct an online survey with 1,000 students as participants.

2.5 Fake News in Business and Management

The Spread of fake news on social media can have significant damage to businesses and brands. Fake news can cause a negative brand image and financial losses. Developing a comprehensive strategy to face the risks associated with fake news carries significant importance for managers. They can define various strategies such as monitoring social media platforms for false information, establishing a crisis management plan, and direct and proactive communications with customers to dispel fake news and rebuild trust. Several examples demonstrate the impact of fake news on companies. In one instance, a widely circulated tweet falsely claimed that Starbucks offered discounts to undocumented immigrants. The company denied the claim and directly responded to users who shared it (Tschiatschek, Singla, Gomez Rodriguez, Merchant & Krause, Tschiatschek et al.). PepsiCo faced a boycott and a 4 percent decrease in stock price after false news about the company circulated on social media, claiming that the company's CEO had told Trump supporters to take their business elsewhere (Berthon & Pitt, 2018). Kentucky Fried Chicken (KFC) selling rats instead of chicken was another fake news circulated in social media (Pal, Chua & Goh, 2017). The company took immediate action to address the situation. KFC responded to the fake news by releasing public statements denying the claim and assuring customers of the quality and safety of their products. Additionally, KFC utilized its official social media channels to directly communicate with customers, debunking the rumors and providing factual information to counter the fake news. The provided examples highlight the consequences of fake news on a company's reputation and financial stability. The rapid spread of fake news can pose challenges for companies in effectively combating it. It is necessary for brand managers to adopt a proactive approach and develop a strategy to address false news and protect their image in the public. Many research papers have studied the impact of fake news on brands and proposed some response strategies (Mills & Robson, 2019; Ryan, Schaul, Butner & Swarthout, 2020; Vafeiadis, Bortree, Buckley, Diddi & Xiao, 2020). Consumer characteristics and factors that influence customer fake news sharing behavior have also been studied by researchers in the field of marketing and psychology (e.g., Chen & Cheng, 2020; Talwar et al., 2019; Weidner, Beuk & Bal, 2020). These studies provide valuable insights for managers and help them understand the effects of fake news on public perception and offer guidance on how to respond to fake news and mitigate its impact.

Table 2.3 provides a summary of relevant papers that address the managerial and marketing impacts of fake news, offering useful findings for brands and managers. This table serves as a valuable resource, consolidating key research in the field and aiding brand managers in navigating the challenges posed by fake news.

2.6 Fake News in Computer Science

In the modern era, one of the most serious challenges that has arisen as a result of the proliferation of information is the spread of fake news. Computer science plays a vital part in offering answers for the challenging problem of identifying and combatting fake news, which is a severe challenge. These solutions are a need in today's digitally connected world. This section of the study of the literature will offer an overview of the research that has been done in the field of computer science on the detection of fake news, as well as an investigation of the methodologies and methods that are utilized in the field currently.

2.6.1 Review Of Fake News Detection Methods

Fake news detection has been a popular topic for researchers particularly, computer scientists, given the huge amount of data available on social networks. One of the important features that has been studied is the linguistic features of fake news. Faustini & Covões (2019) propose a method that relies on text features. They employ K-Nearest Neighbor (KNN), Random Forest, Gaussian Naive Bayes, and Support Vector Machine (SVM) algorithms to identify fake news on social media. Ozbay & Alatas (2020) apply a two-step approach to identify fake news. First reprocessing the data with the term frequency-inverse document frequency (tf-IDF) weighting method and second applying 23 supervised machine learning algorithms on a data set of news stories. Fake news creators often employ bots to create and spread fake news via different channels of social media while concealing their real identity, therefore bot detection emerged as an area of research within the context of fake news (Al-Rawi et al., 2019; Jones, 2019; Ross, Pilz, Cabrera, Brachten, Neubaum & Stieglitz, 2019). Network analysis, anomaly detection, and pattern recognition methods have been used to develop techniques to identify these bots to distinguish between automated accounts and genuine user activity (Al-Rawi et al., 2019). Understanding the characteristics of bots improves the accuracy of fake news detection and prevents rapid spread.

2.6.1.1 Machine learning

Research on fake news is one of the many fields that has benefited significantly from the application of machine learning, which is a subfield of computer science that examines how computers may learn to carry out tasks without being explicitly programmed to do so. Because it is able to process extremely large volumes of information, it is especially helpful for activities involving prediction (Ongsulee, Ongsulee). Numerous publications in the body of research that was examined make use of machine learning and deep learning techniques in order to detect fake information and recognize significant characteristics. Features such as text/content-specific features that are focused on linguistic patterns within the news article or social media posts (Ruchansky, Seo & Liu, 2017), visual and image-specific features are used to identify misleading images (Zhang, Wang & Tan, Zhang et al.), user/account features consider the characteristics of the account sharing the news, including account age, number of followers, and engagement patterns (Shao, Ciampaglia, Varol, Yang, Flammini & Menczer, 2018), propagation features such as speed and patterns of news spread within a social network (Friggeri, Adamic, Eckles & Cheng, 2014), temporal features that include temporal dynamics of news spread like the publication date and the time elapsed since the news appeared (Vosoughi et al., 2018), structural features like the connectivity patterns among users sharing the news (Kumar et al., 2016). Sentiment, readability, and lexical choices are considered linguistic features within the news content (Potthast, Kiesel, Reinartz, Bevendorff & Stein, 2017). Machine learning methods such as Naive Bayes, Support Vector Machine (SVM), decision trees, random forests, and logistic regressions are widely used in fake news detection. These algorithms can learn patterns from labeled data and make predictions based on what they learned. However, one of the drawbacks of such methods is their reliance on manually labeled data. These labels can be affected by human bias. Faustini & Covões (2019) evaluate several machine learning algorithms such as SVM and Random forest to detect fake news in different platforms. They highlight the importance of considering the specific features of platforms to detect fake news. They propose a multilingual approach to be used for detecting fake news in different languages. Elyassami, Alseiari, ALZaabi, Hashem & Aljahoori (2020) employ various machine learning algorithms including Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, and k-Nearest Neighbors (kNN). According to the findings, the ensemble learning framework is superior to the individual algorithms in terms of precision, recall, and F1 score, achieving higher accuracy as a result of its use. Deep learning models are also employed in the fake news detection studies, Rodrigues, Fernandes, Shetty, Lakshmanna, Shafi & others (2022) use Naive Bayes, SVM, and Random Forests to classify tweets as spam or not. They train models using labeled data to predict tweet content attributes like keywords, URLs, and user mentions. The study includes sentiment analysis as well. The authors use CNN and LSTM networks to detect tweet sentiment. They train deep learning models to categorize sentiment as positive, negative, or neutral. They highlight the significance of real-time spam detection and sentiment analysis in fake news detection on Twitter data. Amer, Kwak & El-Sappagh (2022) carry out three experiments: one with machine learning classifiers, one with deep learning models, and one using transformers. In each of the tests, they extract contextual features from articles using word embedding as the primary method. When it comes to accuracy, the results of the experiments show that deep learning models perform better than machine learning classifiers and transformers. In addition to this, the results demonstrate that the LSTM and GRU models have nearly identical levels of accuracy. Khan, Khondaker, Afroz, Uddin & Iqbal (2021) perform a benchmark study in order to evaluate the effectiveness of a variety of applicable machine learning approaches on three separate data sets, where they gathered the largest and most diversified data set possible. They conduct a first-of-its-kind study in which they compare the performance of pre-trained language prototypes with deep learning ones in detecting fake news. Pre-trained algorithms such as Bidirectional Encoder Representations from Transformers (BERT) and others do the best job of detecting fake news, even with a restricted data set. As a result of this, these models are a significantly better option for usage with languages that have a limited amount of sample content, also known as training data. In addition, they carried out a number of studies dependent on the efficacy of the models, the topic of the article, and the total word count of the article.

2.6.1.2 Network analysis

The propagation of fake information is extremely comparable to the transmission of infectious illnesses, and one method that may be utilized to gain an understanding of this process is the utilization of network epidemic models.Vosoughi et al. (2018) conduct an analysis on a data set of rumor cascades, comprising tweets and retweets, and reveal that on social media, fake news travels quicker than true information.Lord Ferguson et al. (2019)develop a framework specifically focused on explaining the propagation of fake news within the health industry. In their work, they highlight the importance of examining the propagation of information to comprehend how both true and false information spreads. While much research has concentrated on the creation of misleading information and the intent of the creators, Giglietto, Iannelli, Valeriani & Rossi (2019) emphasizes the need to shift attention toward understanding the propagation process itself. Further investigations have employed network analysis on Twitter to study the role of spreading groups in the dissemination of fake news. Sela et al. (2019) explore the differences between users involved in highly repeated and lowly repeated cascades and found significant variations in the distribution of retweets. They discover that messages from a few anonymous Twitter accounts had a wider reach compared to those from well-known accounts. Pantumsinchai (2018) provide insights into how claims can be perceived as either fact or fiction based on networks of interactions during major events. Additionally, Papanastasiou (2020) suggests that people are more likely to share the news if their peers have already done so. The significance of comprehending how social influence affects the spread of both truthful and misleading information is emphasized by this study. Overall, by analyzing the dynamics of information spread in relation to fake news, researchers have revealed the rapidity with which false information propagates on social media platforms, the role of anonymous accounts, the impact of social influence, and the need to understand the mechanisms of information dissemination to effectively address the challenges posed by fake news. Table 2.3 summarizes articles in the primary discipline of computer science with the objective, data set, and method used in the respective manuscripts and classifies articles in the computer sciences into three classes with similar goals and details of the corresponding methods.

2.7 Conclusion

A literature study is carried out in this chapter. The vast majority of the articles that were analyzed for this evaluation appeared first in the Academic Journal guide, which is a publication that is recommended by the Chartered Association of Business Schools (ABS). This literature study covers a wide range of papers on fake news, including those from the fields of psychology, management, and marketing. In this chapter, various definitions of fake news as well as a review of theoretical frameworks and methodological approaches have been offered. The investigation into so-called fake news is receiving a lot of focus these days. The proliferation of internet networks and social media platforms has a significant impact on the dissemination of false information. The study of the identification of false news has been approached from a variety of angles by researchers. The prevention of the spread of misleading information, which may result in significant challenges for both people and society as a whole, is the primary goal of the research being conducted in this area. Studies have concentrated on identifying the characteristics of fake news, studying user behavior, and investigating the properties of fake news sources, among other things. The identification of fake news has seen widespread use of several types of algorithms, including those for machine learning, natural language processing, and network analysis. The findings of the study reveal the fact that despite the substantial amount of research that has been carried out in the field, further research in the field is required in the future due to the quickly changing nature of fake news. This study aims to contribute to the development of effective tactics and tools for detecting and countering fake news by expanding upon the current body of information. The identified study openings and constraints drove the framing of research topics, as well as the development of unique approaches, for the purpose of resolving the challenges given by fake news.

Table 2.2 Summary of marketing and business papers

Author	Findings
Berthon & Pitt (2018)	The paper offers managers approaches to survive in the fake news era.
Beuk et al. (2019)	Confirmatory bias influences fake news consumption greatly. Believability can extend the spread of fake news.
Borges-Tiago et al. (2020)	Consumer attitudes toward fake news can be different based on national culture.
Chen & Cheng (2020)	Self-efficacy and media trust are predictors of consumers' ability to recognize fake news.
Di Domenico & Visentin (2020)	The denial strategy effectively reduces the credibility of fake news for low-involvement stakeholders, but high issue involvement individuals prefer the attack response strategy.
Flostrand et al. (2020)	Findings indicate that service brands are at risk of fake news, and managers must implement fake news mitigation strategies.
Lee et al. (2019)	It is essential that employees of a company believe in the credibility of their slogans. Otherwise, this will have negative consequences for the organization.
Long et al. (2019)	A wide range of customers increases the prevalence of fake news and debunking costs.
Lord Ferguson et al. (2019)	Suggests marketing denial tactics that can be effective in the case of fake news diffusion.
Mills & Robson (2019)	Storytelling is a more effective strategy for companies instead of facts and statistics. Companies can use this strategy to clarify fake news.
Nyilasy (2019)	Fake news is created for the benefit of a sponsor. Fake news spreads on advertising-supported social media.
Paschen (2019)	Fake news titles include more negative concepts than accurate news titles.
Robertson et al. (2019)	Power structures influence the ability to respond to fake news for brands. Externally constructed news is challenging for companies to address. Internally created disinformation will cause distrust in the public.
Ryan et al. (2020)	This case study illustrates the power of inaccurate information on businesses and societies.

Table 2.3 Summary of fake news articles in Computer Sciences

Objective	Author	Dataset	Method
Fake news detection	Apuke & Omar (2021b)	Online survey data	Structural Equation Modelling (SEM)
	Faustini & Covoes (2020)	Twitter	Machine Learning (KNN, random forest, gaussian naïve bayes, SVM)
	Ozbay & Alatas (2020)	News data	Text mining methods and supervised artificial intelligence algorithms
	Papadopoulou et al. (2019)	User-generated videos	Machine Learning
	Wu et al. (2020)	Twitter dataset	Deep Learning (neural network)
	Zhang et al. (2019)	News data	A analytics-driven framework
	Elyassami et al. (2020)	Kaggle fake news data	Machine learning
	Rodrigues et al. (2022)	Twitter	Machine learning and deep learning
	Amer et al. (2022)		
	Khan et al. (2021)	LIAR, US election fake news data, Corpus	Machine learning and pre-trained models
Fake news and characteristics of users involved in fake news sharing	Al-Rawi et al. (2019)	Boston University Twitter Collection	Network analysis
	Sela et al. (2020)	Twitter data	Network analysis
	Islam et al. (2020)	Online survey data	Online survey, PLS-SEM, machine learning methods Online survey, PLS-SEM, machine learning methods
	Jang et al. (2018)	Twitter data	Network analysis
	Shin et al. (2018)	Twitter data	Time series analysis

3. SENTIMENT ANALYSIS AND EMOTION EXTRACTION

This chapter includes the sentiment analysis steps and results. Additionally, emotion extraction methods and results are also described. This chapter is organized into the introduction, data set and pre-processing, sentiment Analysis, and emotion extraction sections. The methods and outcomes are included in each section. The conclusion concludes the chapter and provides a comprehensive review of the results.

3.1 Introduction

In the discipline of natural language processing (NLP), sentiment analysis, also known as opinion mining, is used to extract feelings and other subjective information from written material. The extraction of a text's positive, negative, or neutral sentiments through the use of computational tools is what is known as sentiment analysis. Applications of sentiment analysis may be found in a wide variety of fields, including monitoring social media, managing company reputation, assessing consumer feedback, doing market research, and performing political analysis (Pang & Lee, 2008). Strategic marketing is one of the main applications of sentiment analysis. Păvăloaia, Teodor, Fotache & Danileţ (2019) Carry out research on two different firms, namely Coca-Cola and PepsiCo. According to their findings, the emotional responses of customers on social media can impact the purchase behavior of those customers. There are two different ways that sentiment analysis may be applied: lexicon-based and machine learning techniques. In the lexicon-based technique, which is one of the approaches to extracting the sentiment of a given text, a library of recognized sentiments is employed. These lexicons might be classified as either dictionary-based or corpus-based lexicons, depending on their primary source of information. Corpus-based lexicons generate sentiment information from huge text corpora, whereas dictionary-based lexicons assign sentiment scores to words based on pre-defined sentiment values (Pawar, Shrishrimal & Deshmukh, 2015). In this method, the weight that is given to each word is determined by the feeling that it conveys. These values are tallied up often using a process called summation, and the score that is given the greatest value is used to determine the overarching feeling conveyed by the text. There are a great number of dictionaries that may be utilized for scholarly investigations, for as Vader (Valence Aware Dictionary and sentiment Reasoner) (Hutto & Gilbert, 2014), SentiWordNet (Esuli & Sebastiani, 2006), and Textblob (Loria, 2018). The next step of sentiment analysis is to extract not only the sentiments as positive, negative, and neutral but extracting the specific emotions from the text such as anticipation, surprise, happiness, and sadness. These emotions will provide a piece of very detailed information about the content of a given text. For this purpose, one of the most well-known emotion lexicons available is the NRC lexicon, introduced by Mohammad & Turney (2013). This lexicon provides scores for eight basic emotions of joy, trust, fear, surprise, sadness, anticipation, anger, and disgust. In this chapter, we explore the lexicon-based approach to sentiment analysis and examine the performance of different lexicons in extracting sentiment from COVID-19 fake news data. Fake news is often created on controversial topics which can produce emotional reactions in human beings. Baumeister, Bratslavsky, Finkenauer & Vohs (2001) suggests that The negative is always more powerful than the positive, and individuals are far more impacted by adverse circumstances than by favorable ones. Those that fabricate fake news do so with the intention of capturing the attention of individuals and spreading their ideas over a variety of channels all over the world. A COVID-19 fake news data collection is used as the subject of this dissertation, in which sentiment analysis and emotion extraction are performed. The findings will reveal important information regarding the degree to which fake news and real news are distinct from one another in terms of the attitudes and emotions.

3.2 Dataset And Preprocessing Steps

3.2.1 Dataset

During this stage of the research, methodologies for analyzing sentiment are employed in order to determine the degree of polarity between fake news and real news and to make comparisons between the two. In order to accomplish this goal, we are going to use a data collection that is comprised of tweets that contain both fake news and real news (Patwa, Sharma, PYKL, Guptha, Kumari, Akhtar, Ekbal, Das & Chakraborty, 2020). This data set has been collected from Twitter using hashtags connected to COVID-19. It consists of 10,700 English postings that have both true and fake labels. The numbers are quite even, with 5600 genuine news items and 5100 fabricated news items. Figure 3.1 is a screenshot of a partition of the data set that includes tweets and labels of tweets (fake or real). This data set was gathered in September 2020 and includes tweets from August and September 2020.

id	tweet	label
1	The CDC currently reports 99031 deaths. In gen...	real
2	States reported 1121 deaths a small rise from ...	real
3	Politically Correct Woman (Almost) Uses Pandem...	fake
4	#IndiaFightsCorona: We have 1524 #COVID testin...	real
5	Populous states can generate large case counts...	real

Figure 3.1 Screen shot of the dataset (author's own representation)

3.2.2 Pre-processing

In the process of analyzing data, the pre-processing stage is extremely important, particularly for textual data. It is possible for the models' performance to be considerably improved by doing the appropriate pre-processing procedures (Haddi, Liu & Shi, 2013). However, in lexicon-based sentiment analysis, not too many pre-processing steps are required. This is due to the fact that sentiment analysis attempts to establish the overall polarity as well as the sentiments contained inside a text. Social media posts consist of many special characters such as exclamation points and question marks. These characters can carry a meaning or display an intensity in the polarity of the text. Lexicons are able to handle these characters and give scores relatively, therefore, these characters are not removed from the text. Additionally, it is not necessary to transform words into vectors before using lexicons for sentiment analysis. Lexicon-based sentiment analysis performs directly on the text data without the need for vectorization. Figure 3.2 is the word cloud of fake news. The word cloud presents the topics and frequencies that appear most often and significantly throughout the text. The word cloud makes it quite evident that the subjects and terms that come up the most frequently are things like COVID-19, pandemic, lockdown, hospital, government, and vaccination. During the epidemic, individuals had a lot of tough themes and worries, and this figure might offer some insight into those topics and concerns. The next step is to analyze the sentiments of fake and real tweets.

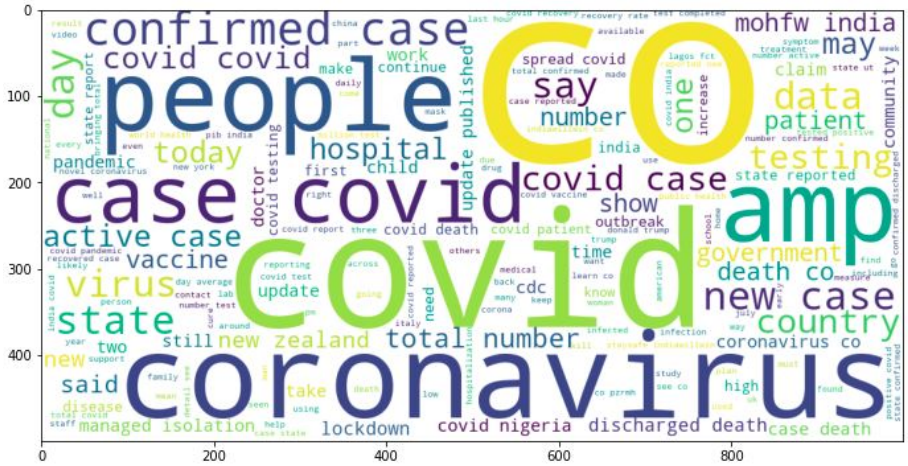

Figure 3.2 Word cloud representing the key themes and frequencies in the data set of fake news tweets (author's own representation)

3.3 Sentiment Analysis

There are two distinct methods that may be utilized while doing sentiment analysis: supervised and unsupervised sentiment analysis. When doing supervised sentiment analysis, a machine learning model is trained using a data set that has been labeled. Generally, if sentiment labels such as positive, negative, and neutral are available in the data set alongside the text, supervised sentiment analysis could be applied to train a sentiment prediction model (Pang & Lee, 2008). Unsupervised sentiment analysis seeks to identify the trends and feelings present in the text without using labels. One method with an unsupervised approach is lexicon-based sentiment analysis, which does not rely on pre-defined labels. A collection of words with related information, such as meaning, semantic relationships, and sentiment polarities, is referred to as a word lexicon. (Manning & Schütze, 1999).Three different lexicons were utilized to identify the sentiments of every tweet in the data set. Vader, Textblob, and SentiWordNet. Figure 3.3 represents the steps to identify the sentiment of every tweet in the data set. Different methods are applied to find the best lexicon. The outputs of the best lexicon would give important information about sentiment differences between fake and real news. These sentiments will be used as input for a fake news detection model.

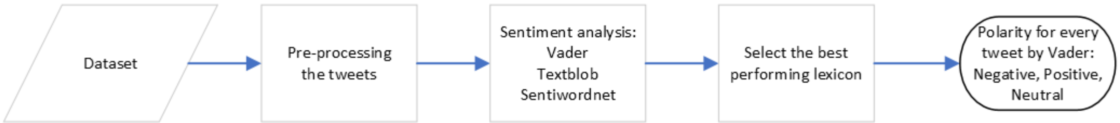

Figure 3.3 Sentiment analysis steps (author's own representation)

3.3.1 Methods

This section introduces and explains the methods of extracting sentiments by lexicons. For this purpose, the lexicons of Vader, Textblob, and SentiWordNet are used. The following subsections contain comprehensive information about each lexicon.

3.3.1.1 Vader

Vader (Valence Aware Dictionary and Sentiment Reasoner) is an open-source lexicon and rule-based sentiment analysis tool. In particular, Vader is tuned in to social media and is attentive to the polarization as well as the intensity of the opinions expressed there.(Hutto & Gilbert, 2014). Each word in the Vader lexicon is assigned a sentiment polarity score ranging from -1 (the most negative) to +1 (the most positive). These scores are based on human-annotated rates. Vader adjusts the sentiment scores by considering degree modifiers such as "very" or "extremely". Upper-case words are treated as more intense. Exclamation points and question marks can also affect the intensity of the sentiment. Valence sifters, such as negations (e.g., "not") or contrasting conjunctions (e.g., "but") can change or reverse a sentiment of a word. All the mentioned aspects are considered to calculate the scores. Vader uses a combination of algebraic and grammatical rules to aggregate these scores.

3.3.1.2 Textblob

Textblob is a library for processing textual data that is written in the Python programming language. It offers an API for natural language tasks including tagging parts of speech, translating, and conducting sentiment analysis. (Loria, 2018). A sentiment polarity score ranging from -1 (most negative) to +1 (most positive) is assigned to each word in the lexicon, and Textblob calculates the polarity of a sentence by taking the average of the scores of the words. The polarity is normalized by dividing the calculated score over the maximum possible score in the lexicon (Loria, 2018).

3.3.1.3 SentiWordNet

SentiWordNet is an opinion lexicon adapted from the Word-Net database. WordNet is a large lexical database that groups words into sets of synonymous words (Esuli & Sebastiani, 2006).

3.3.2 Results

The sentiment of a tweet is determined by the outcomes from three lexicons. The data set now contains a separate column for these findings. The matching column receives the anticipated sentiment as positive, negative, or neutral for each row. Although it was anticipated that the results from the various lexicons would be somewhat comparable, the outcomes are surprisingly considerably different. The breakdown of the three lexicons' positive, negative, and neutral tweets in two classes of fake and real news is shown in Table 3.1. The visual frequency of each label in each lexicon is depicted in Figures 3.4, 3.5, and 3.6.

The results from lexicons indicate that with Vader, the number of fake tweets with negative sentiments outnumbers those with positive sentiments. For real news, there are more positive than negative sentiments. Surprisingly, the opposite trend can be observed in the other two lexicons. These contradictory results demonstrate the necessity of evaluating the performance of three lexicons to determine which one is the most reliable. Using the following methodologies, we compare the efficacy of

Table 3.1 Comparison of three lexicon results

	Fake			Real		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Vader	31.15%	39.31%	29.53%	46.45%	35.20%	18.35%
Textblob	32.23%	21.35%	46.42%	57.05%	18.91%	24.04%
SentiWordNet	41.10%	26.81%	32.08%	53.42%	32.90%	13.68%

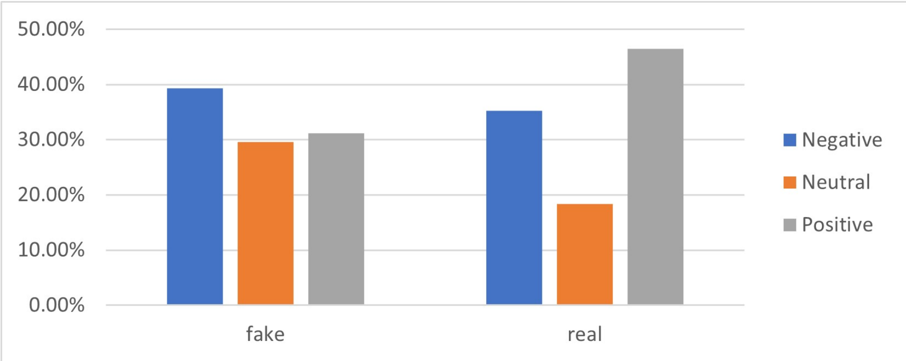

Figure 3.4 Frequency of sentiments in each class with Vader lexicon (author's own representation)

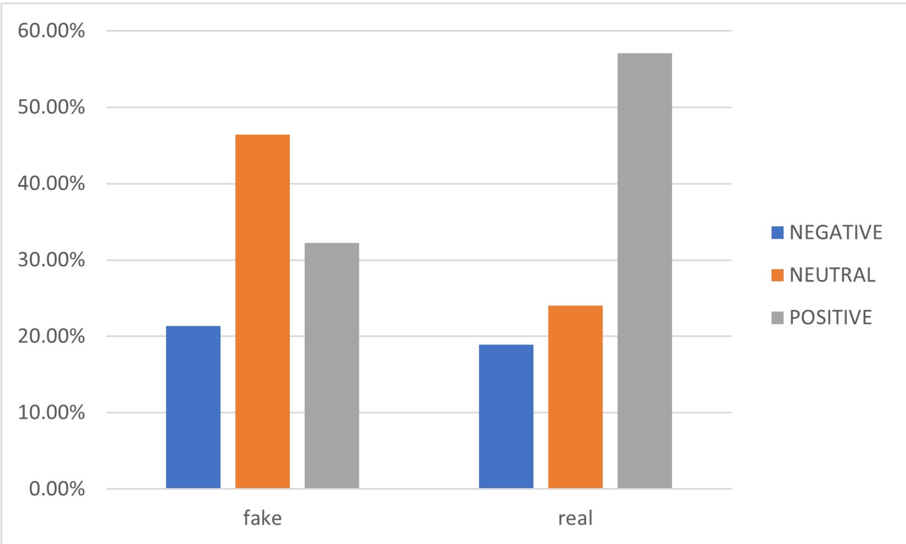

Figure 3.5 Frequency of sentiments in each class with Textblob lexicon (author's own representation)

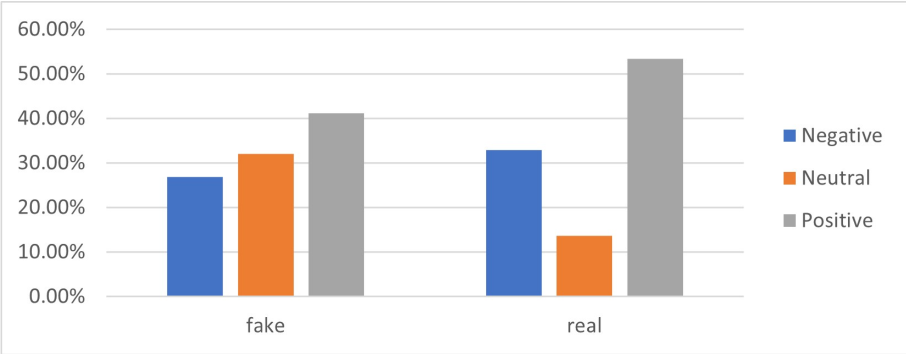

Figure 3.6 Frequency of sentiments in each class with SentiWordNet (author's own representation)

three dictionaries.

- Comparison with human labelling
  1600 rows of the data set are manually classified as positive, negative, and neutral. The three lexicons' results are likewise confirmed using this section of the data set. Performance metrics for each of the three lexicons, such as accuracy and precision, have been determined. By comparing the attitudes that are manually classified with those supplied by lexicons, performance measures including accuracy, precision, recall, and F-measure are calculated. The percentage of correctly categorized cases over all instances is the accuracy. The proportion of true positive predictions (positive instances that are correctly anticipated) relative to all of a model's positive predictions is used to determine a model's precision. It measures how successfully the model can avoid producing false positives. Calculating the proportion of true positive predictions is recall, also known as sensitivity or true positive rate. The F-measure is a statistic that accurately assesses a classification model by integrating recall and accuracy into one score (Powers, 2011). The confusion matrix for each lexicon is shown in Figure 3.7, Figure 3.8, and Figure 3.9. Table 3.2 compares 1600 tweets that are manually classified with the results of three lexicons for the matching tweets to show the performance metrics.

  Vader performed significantly better than the other two lexicons. In order to discover the optimal lexicon, Alternative methods were also considered rather than relying solely on the manually labeled portions of the data because the modest values of the accuracies raised questions about the accuracy and reliability of the labeling.

- Compare misclassifications
  The significance of misclassification may differ. As a result, a tweet that

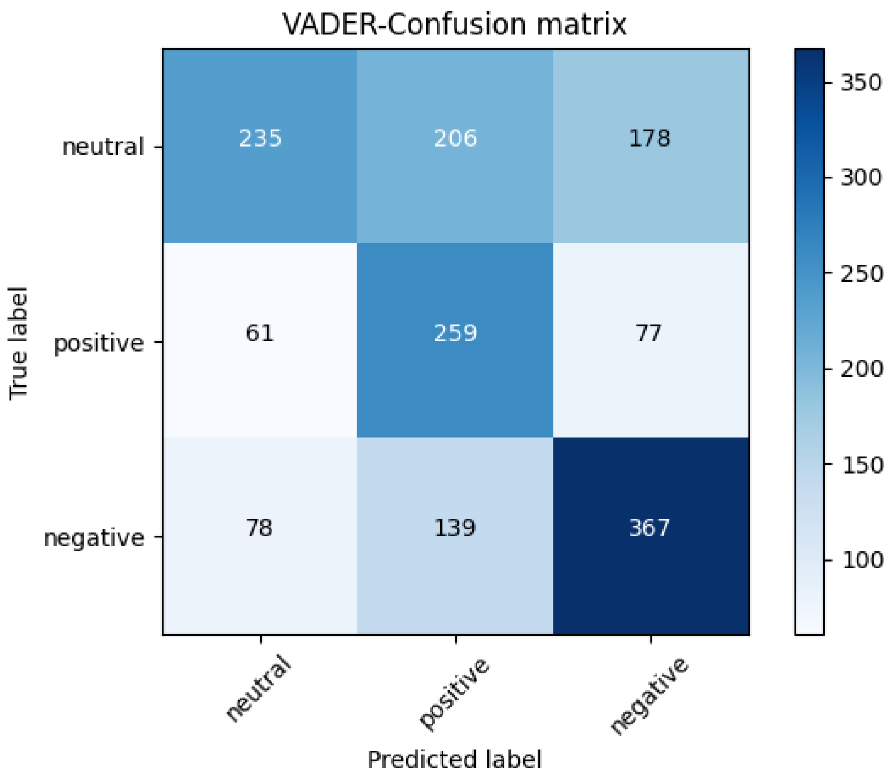

Figure 3.7 Confusion matrix for Vader lexicon (author's own representation)

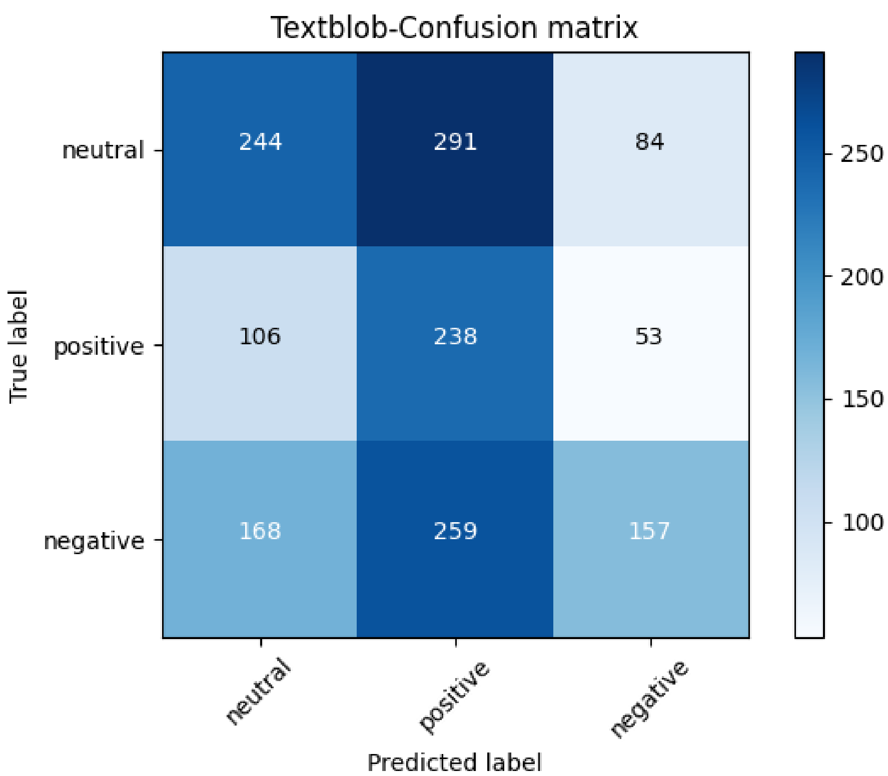

Figure 3.8 Confusion matrix for Textblob lexicon (author's own representation)

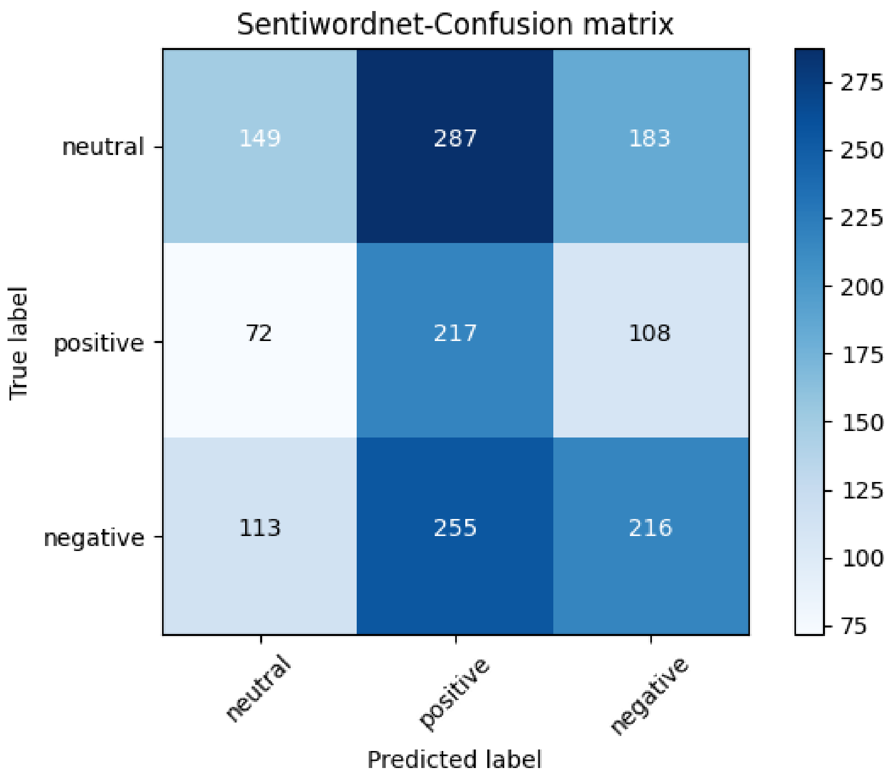

Figure 3.9 Confusion matrix for SentiWordNet lexicon (author's own representation)

Table 3.2 Performance metrics of lexicons

	Vader	Textblob	SentiWordNet
Accuracy	0.54	0.40	0.36
Macro Precision	0.55	0.44	0.39
Macro Recall	0.55	0.44	0.39
Macro F1-score	0.53	0.40	0.36
Weighted Precision	0.56	0.45	0.40
Weighted Recall	0.54	0.40	0.36
Weighted F1-score	0.53	0.40	0.36

is positive but is categorized as neutral is not as important as one that is categorized as negative. I disregarded the neutral portion in favor of comparing categorization metrics. Table 2 includes the performance metrics. In this instance, Vader outperformed the other two lexicons in terms of accuracy with a rather large difference.

- Compare the classification power of sentiments

  The purpose of this study is to find out whether the emotional content of a tweet or news item can be utilized to assess whether it is true or false, as well as how this information may be applied to identify fake news. In light of this, I investigated how lexical output may distinguish between false and accurate

Table 3.3 Performance metrics for two-class classification

	Vader	Textblob	SentiWordNet
Accuracy	0.77	0.55	0.55
Precision	0.66	0.46	0.65
Recall	0.84	0.83	0.45
Specificity	0.75	0.38	0.38
F1-score	0.73	0.58	0.52

news. Additionally, a sizable portion of the tweets in the COVID-19 data set reflect on the quantity of hospitalized, died, and recovered individuals. These tweets don't reflect any particular sentiments or ideas, yet they occasionally do contain both optimistic and pessimistic viewpoints. Therefore, during this stage of the research, the tweets that contain this numerical information are eliminated from the data. As a result, the output of each lexicon served as a feature for categorizing fake and real news. The Random Forest classifying model of the sciket-learn python library was chosen for this purpose (Islam, Liu, Li, Liu & Kang, 2019) given that the Random Forest classifier is suitable for dealing with noisy data in text classification. The train data (80% of data) and test data (20% of data) are separated from the data set. The categorization is done in 3 cases. In the first instance, tweets plus Vader's output serve as the model's input; in the second, tweets plus Textblob's output; and in the third, tweets plus SentiWordNet's output. Table 3.4 presents the three-classification model's accuracy.

Table 3.4 classification scores for lexicons

Features	Random Forest accuracies
Vader scores + tweets	0.86
Textblob scores+ tweets	0.74
SentiWordNet scores + tweets	0.82

Relying on the steps explained, Vader was chosen as the best-performing lexicon Table 3.5 illustrates the sentiment differences extracted from the Vader lexicon in two classes of fake and real on the data.

Table 3.5 Vader sentiments in fake and real classes

Label	Negative	Neutral	Positive
Fake	39.31%	29.5%	31.15%
Real	35.20%	18.35%	46.45%

Fake negatives are more common than fake positives. This supports our initial theory about fake news, which holds that those who write fake news employ intense terms to draw viewers in. Since reliable media outlets typically don't want to incite negative feelings in their readers and attempt to be neutral regarding contentious themes, positive news typically outweighs negative and neutral news in the real news. Naturally, fake news publishers like to express negative words and feelings toward their target point because their usual intent is to criticize or mock an idea, a person, or a business. They are conscious of the impact of bad and negative news. According to Baumeister et al. (2001), Negative experiences have a greater influence on individuals than happy ones because bad is far more powerful than good. According to this psychological phenomena, humans who submit deceptive data do so to appear impressive. During the COVID-19 pandemic, certain hot-button issues gained popularity, including the origin of the virus, various proposed treatments, the government's approach to preventing its spread, and the vaccine. All of these issues encountered fierce opposition. Therefore, there is a great chance that these subjects may generate fake news with negative sentiment.

3.4 Extracting Emotions of Tweets

The extraction of emotions from text is a later step in sentiment analysis. These details will demonstrate whether the text has particular emotions like sadness, anger, or surprise. Several techniques have been put up for extracting emotions from a text, similar to sentiment analysis. Lexicon-based methods rely on a set of words with emotions assigned to each one. Based on the existence and strength of emotion words, these lexicons assign sentiment scores or intensities to words, allowing the computation of overall emotion ratings for texts (Hutto & Gilbert, 2014). The emotions in COVID-19 fake news tweets are extracted using a lexicon-based method in this study. Comparing the emotions extracted from fake and real news would reveal vital details about how the two types of news differ regarding the way the emotions of the text are expressed.

3.4.1 Methods

NRC Lexicon analyzes the text's overall emotional impact. It is composed of over 27,000 terms and is based on the WordNet synonym sets from the NLTK library and the National Research Council of Canada (NRC) affect lexicon (Mohammad & Turney, 2013). The Plutchick model of emotion, often known as Plutchick's wheel of emotion (Plutchik, 1980), is the basis for the NRC Lexicon's design. Robert Plutchik, a psychologist, developed the Plutchik Model. Plutchik suggests that joy, trust, fear, surprise, sadness, anticipation, anger, and disgust are the eight basic emotions. These feelings can be divided into four opposite pairs: happiness-sadness, anger-fear, disgust-trust, and surprise-anticipation. Figure 3.10 is representing Plutchick's wheel of emotion. The intensity is represented by the vertical dimension of the cone; as one moves from the outside to the inside of the cone, their feelings get more intense. The NRC lexicon was used to extract the data set's emotions. The NRC Emotion Lexicon offers sentiment intensity scores for the eight fundamental emotions of anger, anticipation, disgust, fear, joy, sadness, surprise, and trust in addition to emotion categories for each one. Moreover, this model could provide insights into more complicated emotions as well, For instance, Love is the combination of joy and trust. Optimism is a combination of joy and anticipation, and a combination of anticipation and anger could indicate aggressiveness. This classification is a simple modeling of Plutchik's wheel NRC lexicon and provides scores for the eight basic emotions, however looking into a combination of the emotions could also give insight into the more complex emotions. Each emotion has a score between 0 and 1, which represents how strong or intense it is in relation to the word in question. A higher score denotes a more positive relationship with the associated emotion.

3.4.2 Results

3.4.2.1 Emotion categories

Table 3.6 Emotion Distribution

	Emotion (%)							
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
Fake	1.76	2.15	0.56	31.85	0.68	1.81	0.57	8.28
Real	1.11	5.20	0.12	26.52	0.78	3.57	0.83	14.21

Figure 3.11 represents the outputs given from the NRC lexicon.

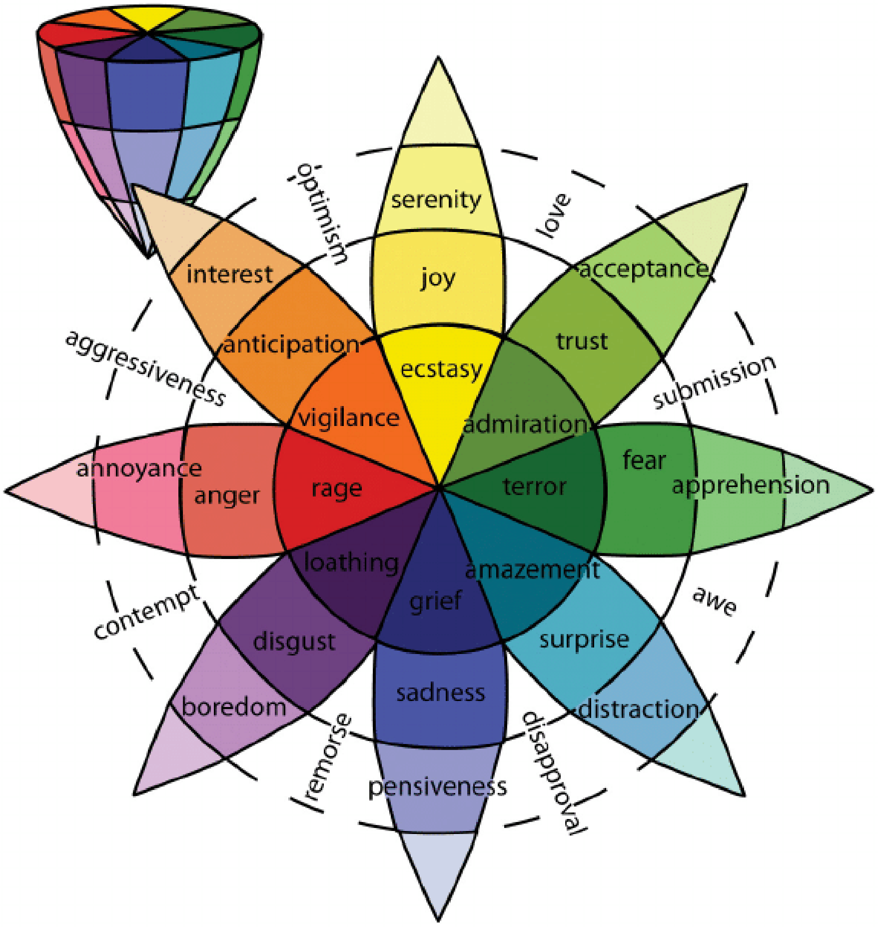

Figure 3.10 Plutchick's wheel of emotion (Plutchik, 1980, pp. 3-33)

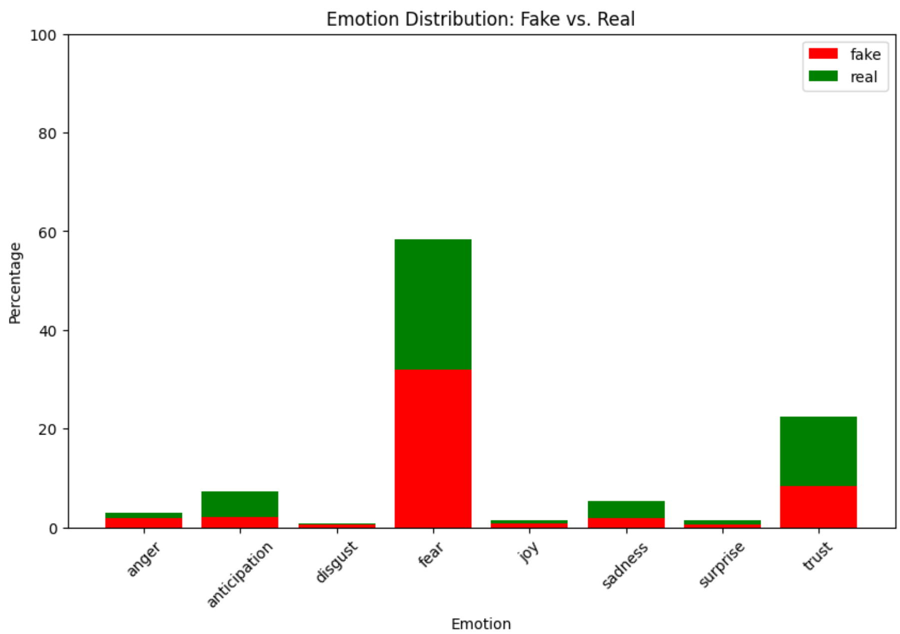

Figure 3.11 Distribution of emotions in two classes of fake and real (author's own representation)

- Anger: Compared to the "real" category (1.11%), the "fake" category had a larger percentage of anger (1.76%).
- Anticipation: Compared to the "fake" category (2.15%), the "real" category had a larger percentage of anticipation (5.20%).
- Disgust: Compared to the "real" group (0.12%), the "fake" category had a slightly larger level of disgust (0.56%).
- Fear: Compared to the "real" group (26.52%), fear is more prevalent in the "fake" category (31.85%).
- Joy: Compared to the "real" category (0.78%), the "fake" category has a lower percentage of joy (0.68%).
- Sadness: Compared to the "fake" category (1.81%), the "real" category has a larger percentage of sadness (3.57%).
- Surprise: Compared to the "real" group (0.83%), the "fake" category has a lower rate of surprise (0.57%).
- Trust: Compared to the "fake" group (8.28%), the "real" category (14.21%) has a higher prevalence of trust.

The emotion that dominates fake news the most is fear. This outcome was anticipated since fake news publishers took advantage of the COVID-19 outbreak to spread alarming information that served their purposes. The real news follows the same pattern, and the most prevalent emotion there is fear, however, the intensity of fear in real news and fake news could be compared. In the entire data set, 26.52% of the stories that mention fear are real and 31.85% are fake. Therefore, in terms of fear feeling, fake news has a larger share than real news. According to the findings, trust in real news is far higher than trust in fabricated news, which is to be expected. Another feeling that has been seen more frequently in fake news than in real news is anger. The next section compares the degree to which each feeling is evoked by two distinct types of news.

3.4.2.2 Emotion intensities

NRC Lexicon rates each of the eight emotions, and the text is given the emotion with the highest rating. This section compares the scores for each emotion's intensity in the two categories of fake and real news. Therefore, in addition to the distribution of emotions, the intensity of emotions is also compared. Table 3.7 displays the average score for every emotion in each category of fake and real news.

Table 3.7 Emotion intensities

	Emotion score (Average)							
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
Fake	0.033	0.231	0.025	0.097	0.028	0.064	0.018	0.097
Real	0.020	0.282	0.015	0.076	0.027	0.064	0.022	0.126

Both types of fake and real news have fear as their predominant emotion, however fake news has a higher intensity score for fear than real news. In every category of fake and real news, trust is the second most prevalent emotion, but in real news, it is more intense than in fake news. Positive feelings like anticipation, surprise, and trust are exhibited more strongly than in fake news. Fake news contains more intense expressions of negative emotions including anger, disgust, and fear. Both classes fairly equally experience happiness and sadness.

3.4.3 Significance Test Results

To determine whether or not the difference in emotions between the two sets of fake and real news was statistically significant, a test of significance was run using the Pinguin statistical program in Python and a two-independent sample t-test. The statistics provided by the t-test are summarized in Table 3.8. The significance threshold for p_values is set at 0.05. For fear, trust, surprise, and anger the p_values are incredibly low. These low amounts of P_values are indicating a highly effective difference. Considering the other metrics as well indicate a significant difference in anticipation, anger, disgust, fear, and surprise. The difference between the two categories of fake and real news, however, seems to be minimal for surprise, joy, and sadness.

Table 3.8 T test results

Emotion	P-value	
Fear	6.57E-12	< 0.05
Anger	4.17E-16	< 0.05
Trust	8.74E-13	< 0.05
Surprise	0.007362	< 0.05
Sadness	0.984772	
Disgust	2.16E-14	< 0.05
Joy	0.318163	
Anticipation	1.86E-39	< 0.05

3.5 Conclusion

In this chapter, a lexicon-based sentiment analysis technique is utilized in order to investigate the feelings evoked by the data set. Three distinct lexicons are utilized in order to generate the sentiment labels of positive, negative, and neutral respectively. After analyzing a number of lexicons with a variety of approaches, the most effective lexicon is chosen. The performance of Vader is superior to that of any lexicon. According to the feelings that were extracted from Vader, fake data has a greater number of negative tweets than good tweets; nevertheless, the situation is exactly the contrary in the real news. It is evidence that one of the characteristics of fake news is that it is negative in tone. Using the NRC emotion lexicon, we are able to determine the precise feelings that are conveyed in the tweets. The NRC emotion lexicon gives points to each of the eight core feelings that are based on Plutchik's emotion wheel. Anger, disgust, anticipation, joy, sadness, surprise, and fear are the eight fundamental emotions that Plutchik (1980) identifies as constituting human emotions. Plutchik also identifies trust as one of these primary emotions. Using the NRC language, we are able to establish ratings for every possible feeling for each and every piece of data. The sentiment with the greatest score is assigned to the tweets that are connected to it. According to the findings, fake news is associated with higher levels of negative emotions, such as fear, anger, and disgust, than real news is. On the other hand, positive emotions such as trust, surprise, anticipation, and joy are more prominent in true news than they are in fake news. This provides support for the primary premise of the study, which states that there are distinctions between real and fabricated news in terms of sentiments and emotions, with fake news evoking far greater reactions than true news does. An examination of the depth of the sensations is carried out by comparing the lexicon's designated emotion ratings to one another. According to the findings, negative emotions such as fear, anger, and disgust are shown more strongly in fake news. This is the case even when the fake news is based on facts. The findings of the statistical test indicate that there is a substantial difference in the emotional responses between the two groups, particularly with regard to the following feelings: anticipation, anger, disgust, fear, and surprise.

4. FAKE NEWS DETECTION MODELS

Sentiment lexicons and emotion lexicons are used in Chapter 3 to construct and add a number of features to the data set. According to the study of Chapter 3, there are major differences between fake and real news in terms of the sentiments and emotions expressed in the text. There is now a data set with significant information that may be utilized for a variety of things, particularly for fake news detection. The effectiveness of these attributes with the COVID-19 fake news are investigated in this chapter using a number of fake news detection algorithms. The introduction part includes a discussion of some of the models utilized in this study as well as an overview of fake news detection techniques. The methods section includes descriptions implemented models. The results section includes the model results, and the conclusion includes a summary of the findings.

4.1 Introduction

Fake news is not a brand new problem that has arisen as a result of social media; it was a huge problem in conventional media as well, but there was no adequate technology to automatically identify them from trustworthy news until recently. The development of new technologies has coincided with an increase in the number of social media platforms that are currently available. Parikh & Atrey (2018) introduce several methods for fake news detection in their article. In the same vein as other classification issues, the use of machine learning techniques has seen widespread use for the identification of fake news (Manzoor, Singla & others, 2019). Depending on the type of data that is accessible, one can use either supervised or unsupervised machine learning approaches to identify instances of fake news (Padmanabhan, Chakraborty, Long & others, 2021). Supervised machine learning performs well when classification labels are available in the data set, so the model is trained and

predicted based on the features of the data that has been learned.
The data set utilized for the analysis of this study includes a category as fake or real. The features extracted in Chapter 3 are performing as inputs for the detection model. The benefit of machine learning models is that the effectiveness of each feature could be evaluated, making it possible to identify the most crucial elements in the model. In most cases, the performance of deep learning models is superior to that of machine learning models. Since they find and extract patterns and features automatically which are not defined as separate columns in the data set. As explained in Chapter 3, not too many pre-processing steps are done for lexicon-based sentiment analysis. Since the language in social media is not an official and standard form of language, users can use many signs such as question marks or exclamation marks to intensify the emotion of the content that they are sharing. However, classification models may function better on textual data if the data is clean. As a result, some pre-processing steps are used before implementing the detection models. The following data pre-processing processes are carried out in this section of the study:

- Removing all characters from the text other than the alphabet
- Lower-casing the letters
- Tokenization
- Eliminating stop words such as "a", "the", "is", and "are" that contribute very little to the overall meaning of the sentence.
- Lemmatization: A lemma refers to the base form of a word, such as "run" being the lemma for variations like "running" or "runs". Lemmatization converts all words to their respective lemma.

Before using the detection algorithms, the correlation between variables is investigated. The findings are shown in Figure 4.1 as a heat-map and in Table 4.1. The correlation table implies that emotions of fear and sadness are highly correlated. There is no other correlation between other emotions. The scatter plot of features are given in Figure 4.2, Figure 4.3, Figure 4.4, and Figure 4.5. All other two by two combinations of the components were studied but as an example, only four combinations of them are included in this manuscript. In these scatter plots, the opposing emotions based on the Plutchik emotion model are chosen for the axis of the plots. The scatter plots fail to reveal any unique interactions or connections between the elements. The association between fear and sadness, which can be handled by the detection models, is the only point worth mentioning. The positive or negative role of these emotions in identifying fake news is discovered by comparing two kinds of models. One which uses the emotion scores as inputs for the fake news prediction model and one that does not include these features.

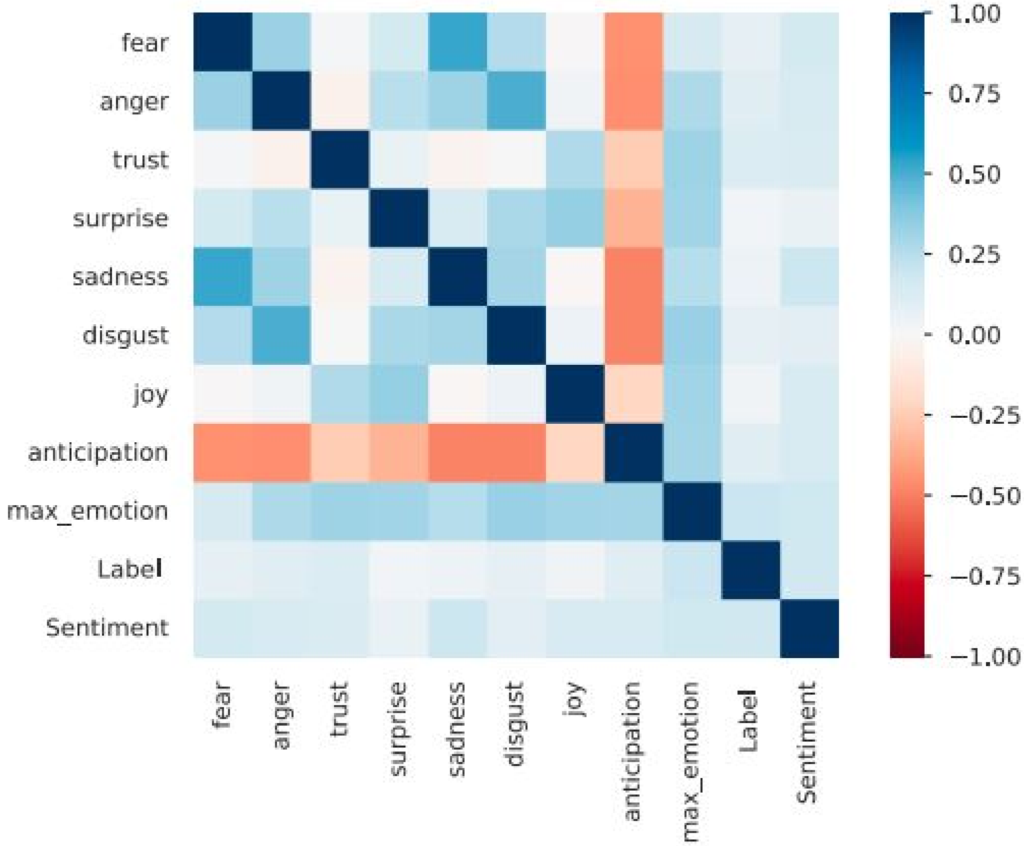

Figure 4.1 Correlation between components of data set (author's own representation)

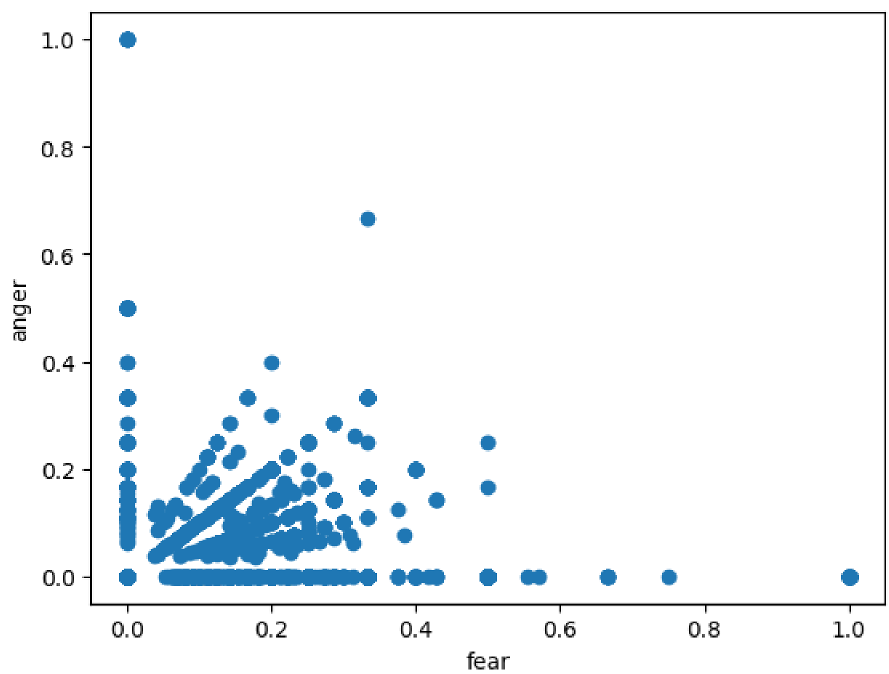

Figure 4.2 Interaction between anger and fear (author's own representation)

Table 4.1 Correlation table

	fear	anger	trust	surprise	sadness	disgust	joy	anticipation	max_emotion	Label	Sentiment
fear	1.000	0.328	0.008	0.151	0.525	0.262	-0.003	-0.438	0.147	0.073	0.154
anger	0.328	1.000	-0.045	0.245	0.317	0.496	0.038	-0.451	0.277	0.104	0.134
trust	0.008	-0.045	1.000	0.067	-0.037	0.002	0.273	-0.248	0.319	0.117	0.126
surprise	0.151	0.245	0.067	1.000	0.136	0.282	0.339	-0.330	0.311	0.030	0.061
sadness	0.525	0.317	-0.037	0.136	1.000	0.303	-0.011	-0.480	0.256	0.049	0.184
disgust	0.262	0.496	0.002	0.282	0.303	1.000	0.054	-0.481	0.331	0.082	0.092
joy	-0.003	0.038	0.273	0.339	-0.011	0.054	1.000	-0.210	0.309	0.039	0.134
anticipation	-0.438	-0.451	-0.248	-0.330	-0.480	-0.481	-0.210	1.000	0.298	0.104	0.133
max_emotion	0.147	0.277	0.319	0.311	0.256	0.331	0.309	0.298	1.000	0.202	0.179
Label	0.073	0.104	0.117	0.030	0.049	0.082	0.039	0.104	0.202	1.000	0.170
Sentiment	0.154	0.134	0.126	0.061	0.184	0.092	0.134	0.133	0.179	0.170	1.000

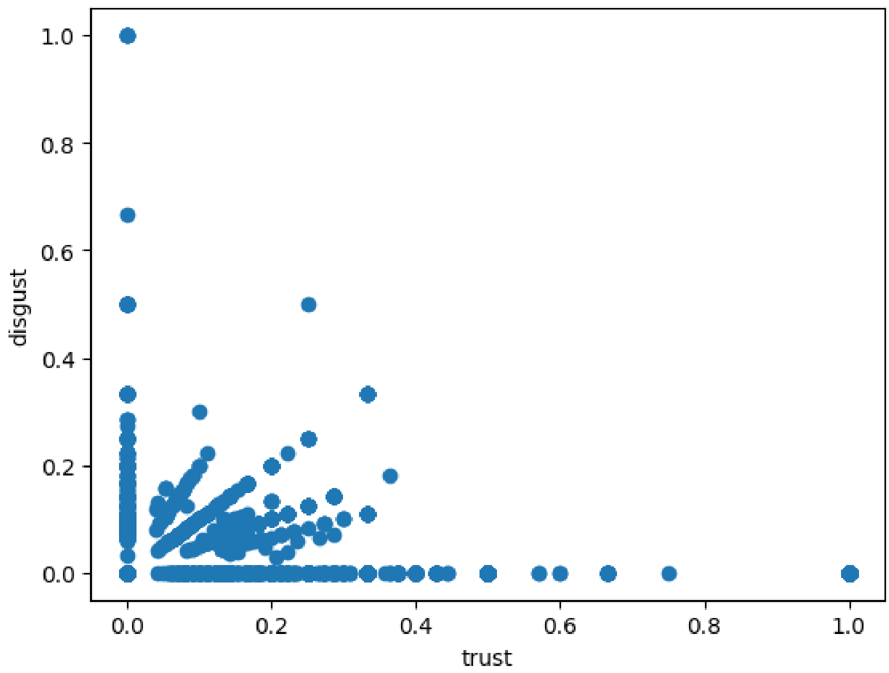

Figure 4.3 Interaction between disgust and trust (author's own representation)

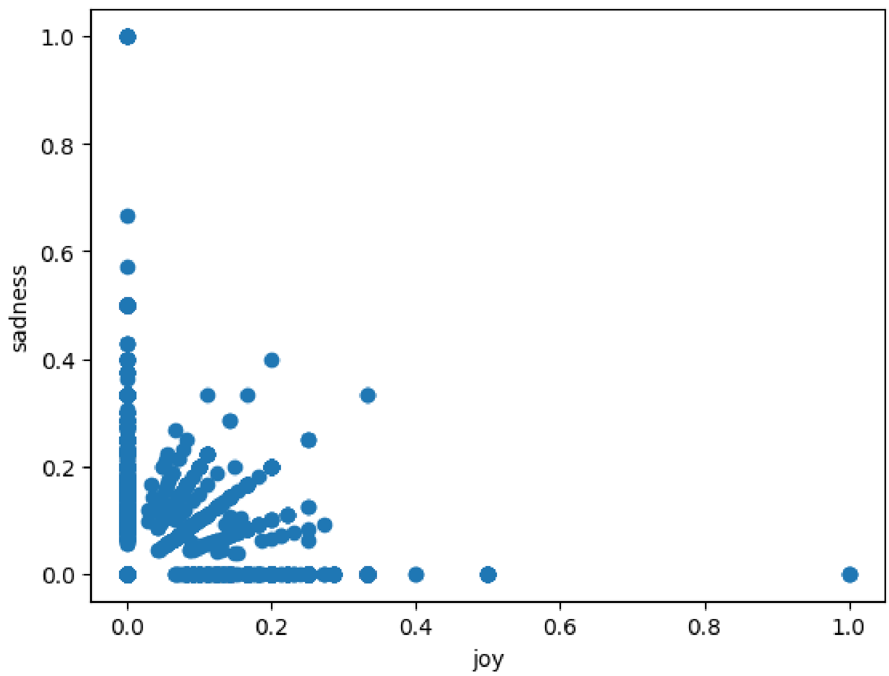

Figure 4.4 Interaction between sadness and joy (author's own representation)

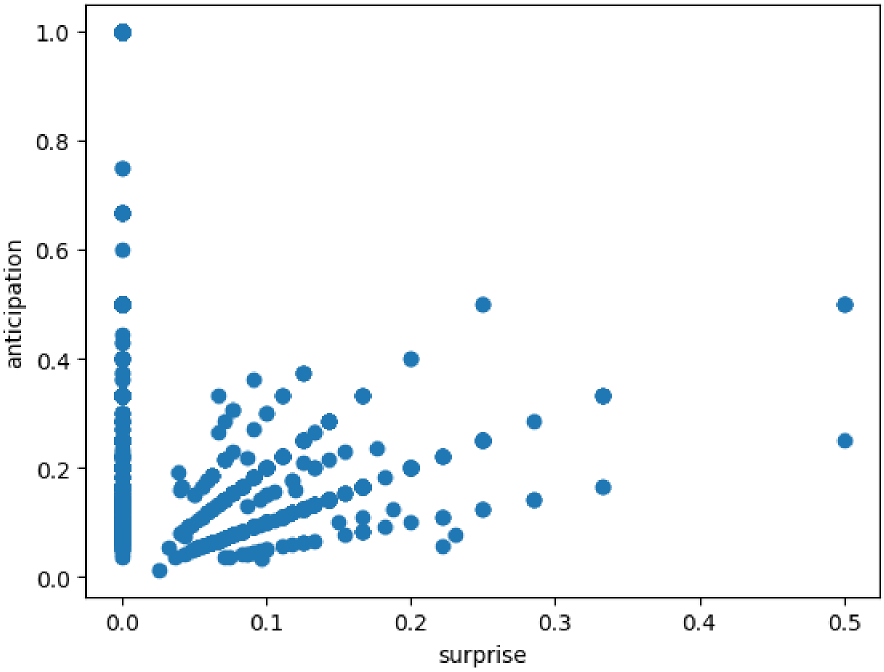

Figure 4.5 Interaction between anticipation and surprise (author's own representation)

4.2.1 Machine Learning

The data set is divided into a train (80%) and a test set(20%). To analyze the data set, three machine learning models are utilized: Random Forest, Support Vector Machine (SVM), and Naive Bayes. The emotion scores extracted in Chapter 3 perform as inputs for these models. Performance metrics of models are compared with and without emotion scores.

4.2.1.1 Random forest

The Random Forest classifier is an example of an ensemble learning method. It works by fitting multiple different decision trees to sub samples of data (Breiman, 2001). These sub-samples are chosen randomly. Random Forest classifiers are less prone to over-fitting compared to decision trees. Random Forest classifiers are popular in text classification problems since they are suitable for handling high dimensional data and they provide feature importance that can help to find the best and simplest classification model and can handle missing data(Breiman, 2001). The number of decision trees, maximum depth and the minimum number of required samples to split a node are the hyperparameters of the Random Forest model that can be tuned. In this research, the random forest classifier of the Scikit-learn python library is used. Here are the hyperparameters that are used in this model:

- n_estimators: 100
- max_depth: The decision trees continue to develop until either every leaf is flawless or every leaf have fewer than min_samples_split samples (Knowledge, Knowledge).
- min_samples_split: 2

4.2.1.2 Naive Bayes

The Naive Bayes classifier solves issues by applying the Bayes theorem to the situation at hand. It has proven to be effective in solving problems such as document categorization and spam filtering. Even with a limited quantity of training data, the Naive Bayes classifier may produce satisfactory results (Zhang, 2004). Despite the fact that the basic assumption of the Naive Bayes classifier is that the features are independent given the class labels, the classifier nevertheless works quite well in reality. This assumption is virtually ever true when dealing with text data. Naive Bayes has a very simple and powerful algorithm and it is very well suited for multi-label classification problems (Zhang, 2004). Naive Bayes classifier of the Scikit-learn python library is used in this study.

4.2.1.3 Support vector machines

Support vector machines, known as SVMs, are a collection of supervised learning algorithms that may be used to categorize data, carry out regression analysis, or locate outliers. SVMs can perform well on high-dimensional data and can handle multi-label classifications. SVM finds the optimal hyperplane to separate the different classes in the input space by solving an optimization problem (Cortes & Vapnik, 1995). In this study, SVM model of the Scikit-learn Python library is used.

4.2.2 Deep Learning

Deep learning models have been very successful in classifying text for a variety of reasons, including the fact that they are able to learn hierarchical representations of data, which enables them to discover patterns in the data that are otherwise obscured from view. Because deep learning models consist of numerous layers, the models are able to automatically learn hierarchical representations of the data they are given. Because deep learning models are able to learn from raw data without any human intervention, the time-consuming process of manually designing features is no longer necessary (Goodfellow, Bengio & Courville, 2016). Deep learning models are able to model nonlinear relationships between the features and predicted classes, and they can effectively handle large-scale data. Deep learning has achieved remarkable success in computer vision, speech recognition, and NLP (Bengio, LeCun & others, 2007). In this research, a deep learning model that has already been pre-trained on the language is utilized in order to enhance the fake news identification model. Along the same lines as the machine learning models, the influence of emotion scores will be investigated under two distinct circumstances: with emotions and without emotions.

NLP models that have been pre-trained have been trained on huge data sets specifically for NLP purposes in order to assist with certain NLP tasks. Language models that have already been pre-trained can be utilized in a variety of contexts and applications, including language translation, named entity identification, sentiment analysis, and part-of-speech tagging. Pre-trained models are becoming increasingly popular for usage in NLP positions due to the fact that they can be implemented more quickly, are more accurate, and need less time to train than custom-built models (Devlin, Chang, Lee & Toutanova, 2018). In this study a pre-trained language model called Bidirectional Encoder Representations from Transformers (BERT) to implement a fake news detection model on the COVID-19 Twitter fake news data set.

4.2.3 BERT

The BERT model is a cutting-edge tool that has been very helpful in a number of different NLP applications. Deep neural networks consisting of numerous layers are incorporated into BERT. It is classified as a transformer-based model, which is a sub-category of the deep learning architecture category. A significant advantage that BERT possesses over other deep models is the fact that it implements a bidirectional learning technique. Because of this, it is able to recognize patterns in the text that exist on both the left and right sides of a word within a phrase. Because of this property of the BERT model, it is able to comprehend the meaning of a phrase as well as the connections that exist between the words. The purpose of BERT is to determine the meaning and context of a text. The architecture of the transformer incorporates many layers of self-attention mechanisms and feed-forward neural networks at various levels. BERT is a useful tool for natural language processing (NLP) tasks such as text classification, named entity identification, and question answering because of the layers that enable it to learn sophisticated linguistic data patterns and connections (Devlin et al., 2018; Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser & Polosukhin, 2017).

BERT is a model that has already been trained, and it has been trained on huge data sets such as those found on Wikipedia and BookCorpus. During the fine-tuning step, the BERT model is applied to particular data in order to understand the unique patterns and connections that are present in that data set. Because of its ability to capture contextual data and construct high-quality word representations, BERT is a helpful tool in many different applications of natural language processing (NLP) (Devlin et al., 2018; Vaswani et al., 2017).

4.3 Results

4.3.1 Machine Learning Results

Table 4.2 indicates the performance metrics of the Random Forest, Naive Bayes, and SVM with including the emotion components and Table 4.3 indicates the same models without including the emotion features. As is clear the machine learning fake news detection models considering emotions features outperform the basic model in accuracy, precision, recall, and F1-score except for the Naive Bayes model. Results show that emotion scores are unable to improve the Naive Bayes detection model. Given the assumptions and fundamental qualities of each model, this might be predicted. Random Forest and SVM are more adaptable models than Naive Bayes that can capture complicated correlations between data features. Random Forest and Naive Bayes are given extra discriminatory strength by additional characteristics. One further justification relies on the assumption that the Naive Bayes model is correct. naïve Bayes models are those that make the assumption that the features being considered are conditionally independent, which means that the presence or absence of one feature does not have an effect on the presence or absence of another feature (Manning, Raghavan & Schütze, 2008). As is obvious, a sentence with negative sentiment includes words with negative sentiment that will definitely affect the assigned emotion of the sentence. As mentioned in Chapter 4, the t-test results indicate that the difference between fake and real news in emotions of joy and sadness is not significant. the detection models also are tested by removing these features. Removing the non-significant features does not improve the model's performance. For instance, the accuracy of the Random Forest model after removing the emotions of joy and sadness dropped down from 0.81 to 0.78. Therefore, we can result that even though they are not significant individually, they have a positive role in the detection model when combined with other features.

Table 4.2 Machine learning fake news detection models with emotions

	Accuracy	Precision	Recall	Specificity	F1-score
Random Forest	0.81	0.85	0.94	0.78	0.89
Naive Bayes	0.49	0.69	0.53	0.08	0.69
SVM	0.76	0.74	0.95	0.53	0.85

Table 4.3 Machine learning fake news detection models without emotions

	Accuracy	Precision	Recall	Specificity	F1-score
Random Forest	0.79	0.87	0.88	0.81	0.87
Naive Bayes	0.66	0.70	0.91	0.35	0.80
SVM	0.71	0.71	0.94	0.42	0.83

The Random Forest classification model gives information about the importance of the features as well. Figure 4.6 indicates the importance of every emotion feature in the model. Anticipation, trust, and fear are the three most crucial features in the Random Forest categorization model. In anticipation, trust, and fear, the difference in the distribution of feelings between the two categories of fake and real news is likewise more significant. It can be argued that the emotions of fear, trust, and anticipation are effective at distinguishing between real and fake news.

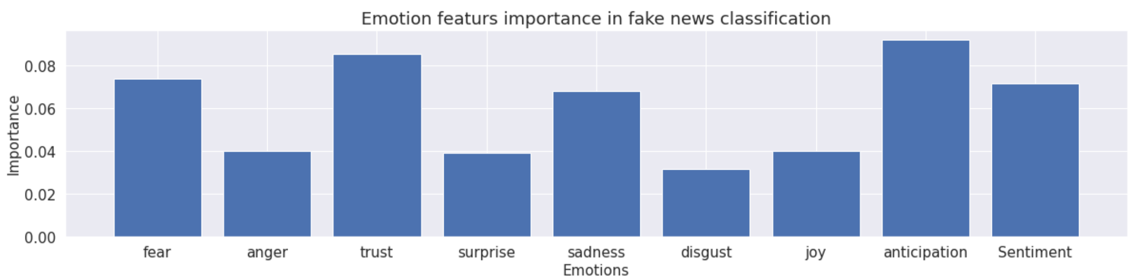

Figure 4.6 Feature importance based on Random Forest (author's own representation)

4.3.2 BERT Results

The BERT model includes a number of pre-processing modules that must be implemented before training can begin. The text input was tokenized with the BERT tokenizer, and padding and truncation were employed to guarantee a maximum sequence length of 128 tokens (128 was used due to computational restrictions; the default for BERT is 512 tokens). The ADAMW optimizer is utilized in this process with a learning rate of 0.00001 in order to perform optimization functions. There are three distinct epochs that make up the training phase. Cross-validation is performed over the data set to determine the optimal number of best epochs. According to the results of the 5-fold cross-validation, the optimal number of epochs for training is 3. Python, a widely used programming language, is employed in the execution of the model on Google Colab. It takes around four hours for each epoch to complete its running time. After training, the model is evaluated on the test set. Performance metrics and confusion matrix of the model are provided in Table 4.4 and Figure 4.7. Like the machine learning models, BERT is employed

Table 4.4 Fake news detection with emotion features using BERT

Accuracy	0.972
Precision	0.983
Recall	0.970
Specificity	0.981
F1-score	0.976

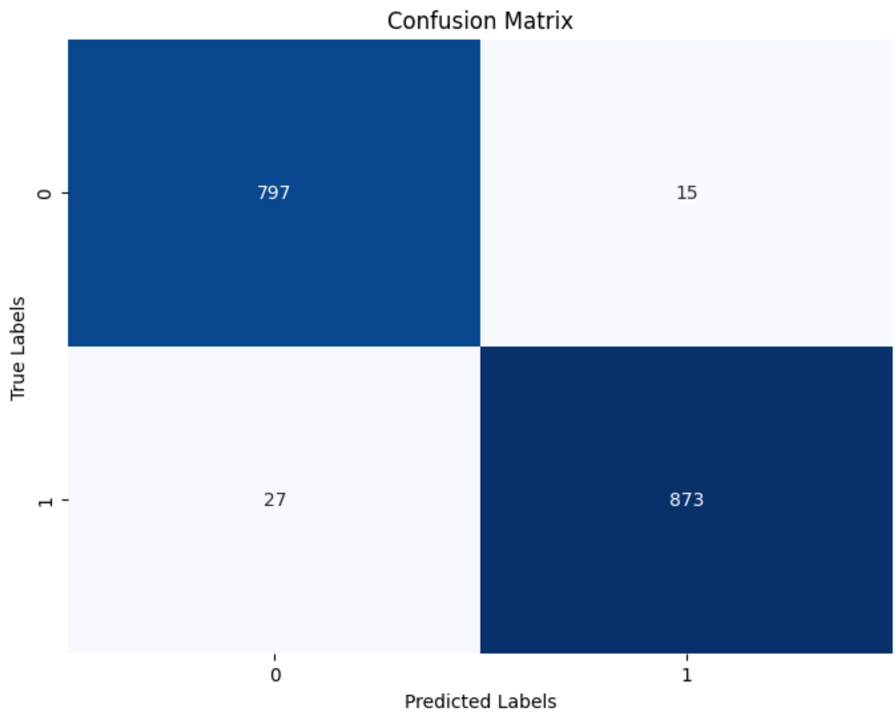

Figure 4.7 BERT Confusion Matrix with emotions(0:fake,1:real (author's own representation)

for data without including the emotion features to see the impact of adding emotion features onto the detection model. The performance metrics for the model without including emotions are presented in Table 4.5 and the confusion matrix in Figure 4.8. Adding emotion features to the deep learning BERT model improved the model accuracy like machine learning models. Unlike machine learning models BERT does not provide explicit feature importance measures. In traditional machine learning models, feature importance is calculated based on the metrics like feature weights, coefficients, or information gain, which can indicate the contribution of every feature in the prediction or classification model. In contrast, BERT model has the ability to learn contextualized representations of words within a given sentence. It encodes the meanings and relationships of words within a context. It's worth noting that deep learning models still benefit from high-quality and relevant data with relevant features since they can better understand the hidden relationship between different features and provide better results (Goodfellow et al., 2016).

Table 4.5 Fake news detection without emotion features using BERT

Accuracy	0.961
Precision	0.981
Recall	0.956
Specificity	0.979
F1-score	0.967

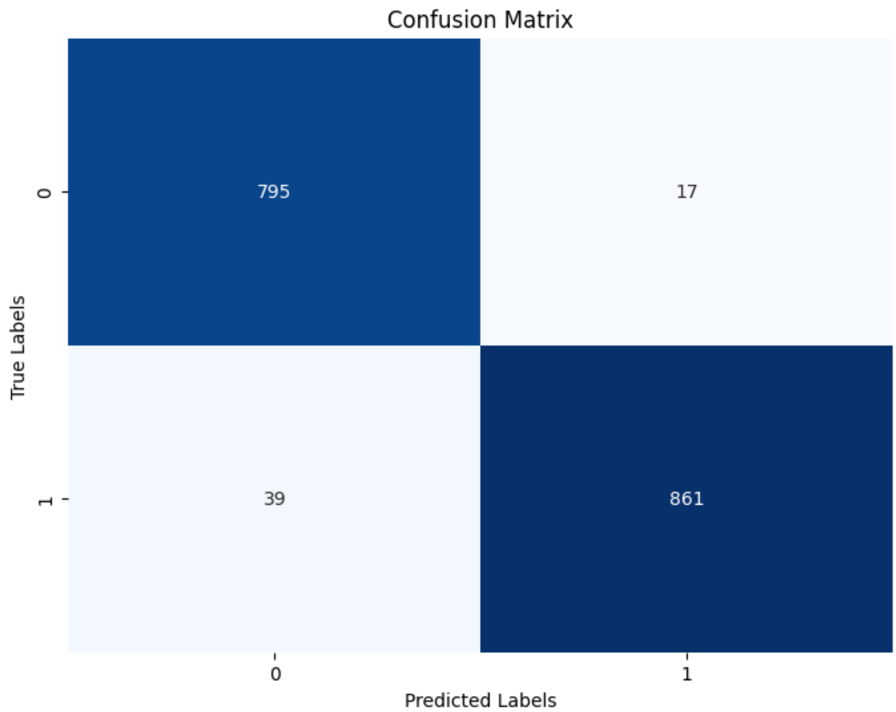

Figure 4.8 BERT Confusion Matrix with out emotions (0:fake,1:real) (author's own representation)

4.4 Conclusion

In Chapter 3, it is discovered that the attitudes and emotions associated with fake and real news are different. More negative feelings and sentiments, are present in fake news. Real news tends to have more positive thoughts and feelings like anticipation, joy, and trust. In Chapter 4, we analyze and assess the efficacy of the emotional distinctions in differentiating between two classes of fake and real. with fake news detection models. To construct detection models with strong predictive capability, machine learning, and deep learning techniques are used.

Techniques from the fields of deep learning and machine learning are used to put the models together that can spot fake news. The models use as their inputs the text of the tweets, the sentiment derived from Vader's vocabulary, and eight emotion ratings derived from the NRC's emotion lexicon. There are three different machine learning models that are used to analyze the data set. These models are Random Forest, Naive Bayes, and SVM. Each model is evaluated using both sets of circumstances, one in which the emotion qualities are incorporated into the model and the other in which they are not. Comparisons are made between these models' predictive performance metrics, which include accuracy, precision, recall, and F1-score, among others. According to the findings, using emotional characteristics in the detection models may improve the classification model's capacity to differentiate between real and fake news.

This finding suggests that it is essential for academics in all domains who are interested in the spread of fake news on social media to pay attention to people's feelings. Additionally, computer scientists who want to construct automatic fake news detection models need to pay great attention to the feelings and particular emotions that are present in false news in order to effectively define models and features for detecting fake news. This is necessary in order to properly describe models and features for recognizing fake news.

5. DISCUSSION

This chapter summarizes the dissertation's initial research aims and clarifies the research's initial goals and motives. The chapter also summarizes key study findings. It highlights research findings, critical insights, and practical results. It addresses the possible benefits, problems, and possibilities of applying research findings in real-world contexts. The chapter ends with some research recommendations based on the study's findings and insights.

5.1 Research objectives and Findings

This study highlights the importance of fake news and details the significant effects it has on economies, society, and individuals. The following research questions are intended to be answered by this study: 1. How do the sentiments associated with real news and fake news differ? 2. How do the emotions of fake news differ from those of real news? 3. What particular emotions are most prevalent in fake news? 4. How could these feelings be used to recognize fake news on social media? The first hypothesis was that the emotional content of real and fake news differ. This argument states that fake news typically has a negative tone compared to real news. Real news is presented in a positive tone, whereas fake news frequently exploits powerful emotions in a negative context.

This study places a strong emphasis on feelings and emotions as essential distinguishing criteria in order to counteract the spread of fake news. 39.31 percent of fake news is characterized as negative, while 31.15 percent is characterized as positive. The publishers of deceptive information have a propensity to choose phrases that more frequently generate negative emotions than good ones. It's possible that they're doing this in order to bring in huge audiences and boost the number of shares. One of the most fundamental and far-reaching laws of psychology is known as the negativity bias. This theory demonstrates that unpleasant news, negative emotions, and negative feedback have a stronger effect than favorable ones (Baumeister et al., 2001). According to the negativity bias theory introduced by Lewicka, Czapinski & Peeters (1992), people tend to value unpleasant experiences more than happy ones. User's actions on social media, such as sharing and retweeting, demonstrate how this idea is put into practice. This theory is used by fake news publishers to get the attention of more people. The other significant finding is that there are more positive tweets than negative ones in the real news category. This is significant since real news is typically provided by reputable sources with the goal of enhancing public awareness and promoting public knowledge.

Moreover, we list the most common emotions seen in fake news and compare the frequency and intensity of these feelings to those found in real news. The emotion that fake news most frequently involves is fear. This is a predictable outcome given that fake news writers took advantage of the COVID-19 outbreak to spread alarming statements that complemented their goals. The same is true for real news, and fear is the most prevalent emotion in real data. However, over the entire data set, 31.85% of news stories, including fear stories, are fake, while 26.52% percent are true. Therefore, in terms of the fear factor, fake news has a larger share than real news. The expression of anger is yet another feeling that has been seen more frequently in fake news. A sign that someone is trying to fool you is when they use harsh or furious words. According to the findings as a whole, fake news is associated with higher levels of negative emotions, such as fear, anger, and disgust. On the other hand, positive emotions such as trust, surprise, anticipation, and joy are more prominent in true news than they are in fake ones.

The intensity of the feelings is examined by comparing the emotion scores offered by the lexicon. The results show that fake news expresses negative emotions like fear, anger, and disgust more strongly than real news. The findings of the statistical test show that there is a significant difference between the two groups, particularly for the feelings of anticipation, anger, disgust, fear, and surprise. Fake news detection models are implemented in this study to evaluate how well emotional differences can distinguish between fake and true news. Machine learning and deep learning approaches are utilized to build detection models with great predictive power. The results imply that adding emotion variables to the detection models can improve the classification models' capacity to distinguish between real and fake news. The fundamental hypothesis of this research is supported by every analysis and computation. In conclusion, the feelings and sentiments associated with fake news and real news are different. Extracting these feelings can help distinguish between fake and real news because fake material entails far more strong, negative, and intense emotions than real news.

5.2 Implications and Applications

5.2.1 Theoretical Implications

This research helps to enhance and create techniques for recognizing and analyzing sentiments in connection to fake news. It contributes to this improvement and development in a number of ways. This work contributes to a better understanding of the ways in which feelings may be used to generate, alter, and spread misleading information.

By examining the feelings that people convey in their tweets, it is possible to discover early warning indicators of the spread of fake news. To gain a better theoretical grasp of how emotions are used to promote fake news on social media, one must first get a better understanding of how emotions are used to propagate false news on social media. This will help increase one's ability to comprehend how emotions are used to influence ideas and beliefs through the dissemination of fake news. Conducting an investigation into the feelings communicated by social media platforms is one method for achieving this goal. When individuals are exposed to incorrect information, the study of the emotional components of fake news can contribute to the growth of theoretical understanding of the ways in which sentiments impact the thinking and judgment of individuals. By gaining an understanding of the psychological aspects of fake news stories, the potential exists for social media platforms to develop strategies that reduce the exposure or reach of such stories.

5.2.2 Managerial Implications

In order to battle fake news and avoid the potential effects of it, it is vital to establish effective techniques that may be used against the publishers of them. It is essential for organizations and enterprises to have these procedures in place, regardless of the possibility that they could become targets of fake news on social media. The most efficient way of expressing news to attract many audiences can be found by studying the emotions of the texts that are shared and believed by many people. Disclosing more detailed features about fake news can help develop existing fake news detection methods, improve effective strategies to combat fake news, and promote critical thinking among social media users.

5.2.3 Societal Implications

Disinformation and misinformation are both types of fake news, but the distinction between the two depends on the reason that they were created in the first place. Misinformation is the term for inaccurate information that is spread unintentionally, whereas disinformation is the term for “false information that is purposely spread to deceive people" and targets a certain idea, person, business, or political party. The research’s methodology can contribute to identifying the purpose behind the creation of fake news and distinguishing between intentional disinformation and unintentional misinformation. Hesitancy to be vaccinated was one of the most serious problems that was made worse as a result of the widespread dissemination of fake news during COVID-19. On various social media platforms, a number of myths concerning COVID-19 vaccines were circulated (Griffith, Marani & Monkman, 2021; Thelwall & Thelwall, 2020), resulting in very serious problems for society. As another example, it is asserted that COVID-19 contains microchips and is used to monitor or modify the behavior of individuals. This conspiracy theory had the potential to attract a large audience, but it was not supported by any scientific evidence (World Health Organization (WHO), 2021). The individuals who subscribe to this conspiracy theory do not get vaccinated, and they spread the word about it across various social media platforms, where they gain a lot of attention. The COVID-19 vaccines, on the contrary, have been shown in a number of studies to be risk-free (American Society for Reproductive Medicine (ASRM), 2021). These are only some of the issues that may become much more serious if, at this crucial time, incorrect information were to be spread over social media platforms. It is possible to increase people’s awareness when they come across such posts and material by using the level of intensity and sentiment of the emotions that are conveyed in social media postings as indications of fake news. These indicators may be utilized in automatic models that detect fake news, or they can be used to raise people’s awareness.

This research not only contributes to the understanding of fake news in the midst of a global crisis, but it also has the potential to be put to use in educating individuals to help them combat potential issues that may arise in society. The method of research that is suggested in this investigation does not restrict itself solely to the content of the COVID-19 study. The findings and methodologies can be implemented into any application that seeks to comprehend and recognize fake news.

5.3 Research Limitations

The research is conducted using a COVID-19 Twitter data set, which only covers a portion of the entire pandemic's time period. Although this study is a pioneering effort in the field, it only examines the eight most fundamental emotions based on Plutchik's emotion model and it is not giving information about the more complex emotions that are combinations of the eight basic ones. Furthermore, the hypotheses and assumptions of this research could be examined in other crisis situations than COVID-19 for more inclusive crisis preparedness. Another drawback of the study is that the sample of data utilized in this investigation is comprised of tweets written in English, the majority of which were authored by native English speakers. The emotion scores in different languages can be different because of some specific characteristics of every language. The difference between fake news and real news is investigated in this study, and the findings are analyzed using sentiment and emotion lexicons. Lexicon-based sentiment analyses, despite being effective for a wide variety of applications, are subject to certain constraints. Lexicons, for example, might not include all of the possible terms in a given language's vocabulary. Since words can have different sentiments depending on the context in which they are used and cultural and linguistic variations can affect sentiment perception and interpretation, lexicons are less effective when applied across a variety of contexts. In this study, lexicons that are adequate and appropriate for the casual language utilized in social media have been chosen. The effectiveness of these lexicons can vary greatly depending on the task at hand. Various approaches are taken in order to identify the lexicon that is most effective for the particular endeavor of analyzing the emotional content of fake news. When it comes to lexicons for specific emotions, there are not a lot of options to choose from, the NRC emotion lexicon is selected because it is frequently utilized in academic research. In order to determine whether or not the outcomes and differences between the two samples of fake and real news are significant, a significance test is used between both samples. Calculating and comparing several performance measures of machine learning models, such as accuracy, precision, recall, and F1-score, is done in order to evaluate and compare different fake news detection models. According to the findings, there is a significant distinction between fake news and real news in terms of emotions, and emotions can assist with the process of detecting fake news.

5.4 Future Directions and Recommendations

The COVID-19 pandemic is an example that demonstrates despite the progress that has been achieved in science and the application of modern technology, people are still uncomfortable with crisis circumstances and may respond irrationally to them. This is the case even though the pandemic occurred in the 21st century.Fake news has the ability to spread further and have more destructive repercussions than it did in the past, which is particularly concerning given current circumstances. In order to effectively combat fake news in similar situations in the future, During a time of global crisis, it is absolutely necessary to have a solid understanding of the specific characteristics of fake news. Acquiring this level of comprehension is required in order to properly resist fake news. In the long term, the execution of an academic research that is more comprehensive on this subject will result in enhanced resources being made available for the construction of plans and road maps. Regardless of the fact that there have been different endeavors and efforts made in research to identify fake news, there is still a need for more precise models and tools that people can use to identify fake news. The detection models will surely benefit from the provision of human-labeled data sets. To extract these characteristics and use them in detection models, research must concentrate on extracting fake news characteristics. Further research might be done on the significance and influence of linguistic and semantic elements, feelings, emotions, and propagation on the detection of fake news.
The emotions, which serve as the primary focus of this research, are also a topic that calls for more study and investigation in the years to come. A single piece of writing might evoke a number of distinct feelings, and certain configurations of those feelings could be an additional and possibly more significant evidence of the presence of false news. For instance, the presence of the fear feeling in conjunction with anticipation may be an indication that what is being expressed is not true. Emoticons are yet another element that, if used correctly, might be of assistance in spotting fake news. A deeper comprehension of feelings, as well as the distinction between real and fake news, may result from doing an analysis of posts on social media while also taking into account the emoticons used.
Culture has a significant impact on linguistic structure. As a consequence of this, it is difficult to generalize the findings from the individuals who speak English to the

rest of the globe. Studies of fake news that are conducted in more than one language or culture might make a significant contribution to the fields of psychology and fake news. Fake news pertaining to certain subjects might potentially be researched and contrasted across a variety of legal systems and cultural contexts. For instance, regarding the issue of vaccine skepticism, as well as the effect that the propagation of false information regarding vaccinations has had in various jurisdictions, and how individuals react in terms of getting vaccinated.

The dissemination of fake news may occur over a variety of platforms, and the examination of a number of these channels can result in a more in-depth comprehension of the validity of the information. The present detection models may be improved by the addition of fake news detection models that expand existing detection approaches to integrate additional modalities, in addition to text, such as photos, videos, and audio. In addition, the development of models that are able to offer coherent explanations for their conclusions can assist consumers in comprehending why a specific piece of material has been identified as being of a deceptive nature. It is also recommended that future research on the identification of fake news explore and attempt to reduce the effects of any biases in fake news detection algorithms. This will ensure that the models do not unintentionally discriminate against particular groups or points of view.

Further research might examine the causes, motivations, and cognitive aspects that make people susceptible to fake news, the cognitive biases that affect their perception, and the psychological impacts of exposure. Data analysts and psychologists should collaborate on human-based and internet-based data problems. This partnership could reveal fake news's origins, distribution, and effects. Results that are more relevant and to the point, as well as findings that are more generalizable and trustworthy, may be obtained by the combination of several research methodologies, such as interviews, experiments, and surveys, with analysis of social media.

It is vital to discover management strategies that can be applied by companies in order to detect and restrict the impact of fabrications on their brand or company and to study the best approaches to managing such situations. This is a critical step in the process of identifying the best ways to manage such situations. Utilizing historical data or conducting experimental studies are two ways that more research may give direction about the response techniques that have the highest likelihood of being successful for companies.

There are moral questions that need to be asked about the responsibility of content authors, social media, as well as society in general when it comes to fake news. Understanding the ethical dimensions of false news, such as the balance between the right to free speech and the need to disseminate information in a responsible manner, is necessary for the development of ethical principles and regulations that are designed to solve the challenges posed by fake news.

6. CONCLUSION

The objectives of this study are to examine how emotions may help to detect fake news; what the distinctions are between fake news and real news in terms of sentiments and emotions; and to emphasize the crucial role that emotions play in fake news detection methods on social media. This research is a case study on the COVID-19 epidemic. The quick transmission of fake news raises major concerns and poses a threat to public health and social well-being, particularly in the midst of such a widespread disaster. The purpose of this research is to examine how fake news was distributed through social media during the pandemic. The primary aims and objectives of this research have been attained as a result of the route that this research has taken. The utilization of sentiment and emotion lexicons gives information that sheds light on the ways in which fake news and real news are distinct in terms of the precise feelings that they elicit.

Sentiment analysis of fake news reveals that publishers of fake news on social media employ negative sentiments more than positive sentiments Martel, Pennycook & Rand (2020), whereas in real news positive sentiments are more widespread than negative sentiments. Eight basic emotions of anger, anticipation, joy, disgust, surprise, sadness, fear and trust introduced by Plutchik (1980) are extracted. The prevalence of fear, disgust, and anger among other negative and powerful emotions, is significantly higher in fake news. The true ones contain far more instances of more positive and joyful feelings, such as joy, trust, surprise, sadness, and anticipation. Additionally, the difference in the included emotions is not restricted to the distribution of the emotions; the emotions also differ in terms of strength, with negative emotions like as fear, anger, and disgust being exhibited more forcefully and passionately in fake news . The models that have been implemented in this work for the purpose of detecting fake news suggest that extracting and adding emotions into automatic fake news detection algorithms might potentially improve their accuracy. Although there have been numerous research and attempts to identify fake news, there is still a need for more precise models and tools. To extract these properties and use them in detection models, research must concentrate on the characteristics of fake news. This study advances the area by highlighting the significant effect of emotions in fake news detection. This study reveals the precise emotional distinctions between fake and real news, which have been shown to be an effective indicator of fake news and a feature for classifying it. Additionally, this research suggests sentiment and emotion lexicons as a practical method for identifying sentimental and emotional differences between true and fake news. Machine learning and deep learning models are used to implement fake news detection models. Results indicate that deep learning surpasses machine learning in terms of classification accuracy and precision. This study has contributed significantly to the field of fake news detection. Research objectives are addressed and research questions are responded by examining the sentiments and emotions of fake and real news. This study adds to the existing corpus of knowledge by identifying emotions as a significant indicator of fake news.

Fake news is a multidisciplinary field of study. Researchers from a variety of disciplines have the potential to make significant contributions to this topic by posing appropriate research inquiries. Scholars in the fields of psychology and the social sciences, for instance, have the opportunity to investigate the goals and objectives of those who produce fake news. Academics in management have the potential to develop useful solutions for corporations to use against fake news. Lawmakers have the ability to set laws that would effectively stop the propagation of fake news on social media platforms. In addition, the contribution that may be made to the existing body of literature by scholars working together who are experts in diverse fields might be quite significant.

During the course of conducting this research, I have experienced personal development and gained invaluable insights, both of which have contributed to the formation of my perspective on fake news. Through participating in this study, I have gained a deeper understanding of the variety of aspects of fake news, how they are expressed, and how they spread. In spite of the initial difficulties that arose throughout the process of gathering and analyzing data, I became aware of the requirement to modify my strategy and investigate several approaches. As I get to the end of this research endeavor, I have come to the conclusion that the findings and conclusions have wider implications than just in the academic world. My honest hope is that the findings of this study will provide useful information that may be used to develop policies, initiatives, or practices that will have a good effect on fake news combat.

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