



**Arabic Sentiment Analysis for Gulf Opinion Leaders using
a Deep Learning Approach Case Study: Covid-19-22**

تحليل المشاعر العربية لقادة الرأي في الخليج باستخدام دراسة حالة لنهج التعلم
العميق: Covid-19-22

by

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ABSTRACT

The COVID-19 pandemic has had a profound impact on global health and has affected various populations worldwide. In the Arab world, social media has emerged as a critical platform for expressing opinions, sharing information, and disseminating news related to COVID-19. However, the proliferation of false information and the spread of fear and panic on social media have created a significant problem. This study aims to investigate how Arab populations, including both opinion leaders and the general public, have responded to the COVID-19 pandemic on Twitter. The research focuses on analysing sentiment and developing a deep learning model to detect real news associated with the pandemic in Arabic text. By gathering and analyzing data from Gulf countries, the study provides insights into the sentiments expressed and contributes to understanding how opinion leaders and the general public engage with COVID-19 on Twitter. Additionally, the study evaluates the efficacy of the deep learning model in combating misinformation and highlights the significance of sentiment analysis and news detection in the Arabic language. Data collection was conducted using Twitter's API, focusing on Arabic tweets from Gulf opinion leaders, utilizing specific keywords, hashtags, and user accounts related to COVID-19. The testing phase involved collecting 100,000 tweets from January to June 2022, with an emphasis on quality and relevance, including opinion leaders with significant follower counts and those recognized for their expertise or influence in the field. Overall, this research contributes to understanding the response to COVID-19 on Twitter and provides valuable insights into sentiment analysis and the detection of real news in Arabic text.

Keywords: Covid-19, deep learning, sentiment analysis, deep learning models, approaches, Gulf opinion, leaders opinion, social media, twitter, sentiments, Arabic language.

ABSTRACT (in Arabic)

كان لوباء COVID-19 تأثير عميق على الصحة العالمية وأثر على العديد من السكان في جميع أنحاء العالم. في العالم العربي ، برزت وسائل التواصل الاجتماعي كمنصة مهمة للتعبير عن الآراء وتبادل المعلومات ونشر الأخبار المتعلقة بـ COVID-19. ومع ذلك ، أدى انتشار المعلومات الكاذبة وانتشار الخوف والذعر على وسائل التواصل الاجتماعي إلى خلق مشكلة كبيرة. تهدف هذه الدراسة إلى التحقيق في كيفية استجابة السكان العرب ، بما في ذلك قادة الرأي وعامة الناس ، لوباء COVID-19 على تويتر. يركز البحث على تحليل المشاعر وتطوير نموذج التعلم العميق للكشف عن الأخبار الحقيقية المرتبطة بالوباء في النص العربي. من خلال جمع وتحليل البيانات من دول الخليج ، توفر الدراسة رؤى ثاقبة للمشاعر التي تم التعبير عنها وتساهم في فهم كيفية تفاعل قادة الرأي والجمهور مع COVID-19 على Twitter. بالإضافة إلى ذلك ، تقيم الدراسة فعالية نموذج التعلم العميق في مكافحة المعلومات المضللة وتسلط الضوء على أهمية تحليل المشاعر وكشف الأخبار باللغة العربية. تم جمع البيانات باستخدام واجهة برمجة تطبيقات Twitter ، مع التركيز على التغريدات العربية من قادة الرأي الخليجي ، باستخدام كلمات رئيسية وعلامات تصنيف وحسابات مستخدمين متعلقة بـ COVID-19. تضمنت مرحلة الاختبار جمع 100000 تغريدة من يناير إلى يونيو 2022 ، مع التركيز على الجودة والأهمية ، بما في ذلك قادة الرأي الذين لديهم عدد كبير من المتابعين وأولئك المعروفين بخبرتهم أو تأثيرهم في هذا المجال. بشكل عام ، يساهم هذا البحث في فهم الاستجابة لـ COVID-19 على Twitter ويقدم رؤى قيمة حول تحليل المشاعر واكتشاف الأخبار الحقيقية في النص العربي.

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CHAPTER 1: INTRODUCTION

1.1 Background and Research Context

The COVID-19 pandemic has become one of the most significant global health crises of the modern era, with widespread impact on all aspects of life. The pandemic has affected different populations in different ways, and it is essential to understand how different groups are responding to the crisis. In the Arab world, the pandemic has been no exception, and social media has become a crucial platform for expressing opinions, sharing information, and disseminating news related to COVID-19 (AlTarrah et al., 2021). On the other hand, social media has evolved into an important tool for communication and expression of emotions, due to the fact that language reflects multiple components that are rooted in cognitive linguistics, psycholinguistics and sociolinguistics (Tsao et al., 2021). People can express their feelings on sites such as Facebook, Twitter, Instagram, and YouTube. According to Radwan (2020), the COVID-19 pandemic caused more than just the virus, as there was a general sense of fear and panic as well as the spread of false information on social media. This created a huge problem worldwide, prompting research to find a way to curb the wrong news. During the COVID-19 epidemic, social media had a significant influence on public opinion and the sharing of information. Social media platforms have revolutionised the way information is exchanged, debated, and consumed as a potent and easily available communication tool. Like many other places, the Arab world has seen how social media has influenced public opinion and the spread of information about the epidemic. The democratisation of knowledge is one important way that social media has an influence on public opinion. Social media platforms, in contrast to conventional media outlets, enable people to actively participate in influencing public conversation. On a variety of facets of the pandemic, including governmental actions, healthcare initiatives, and socioeconomic ramifications, people can express their insights, experiences, and opinions. Individuals are now more empowered and have a more sophisticated perspective of the situation as a result of the free flow of information and the freedom to voice different points of view. In order to promote social justice and magnify the voices of those who are marginalised, social media has been extremely important. Health disparities, economic inequality, and

institutional racism have all gained attention as a result of the epidemic. Social media platforms have given activists, grassroots groups, and individuals a forum to advocate for change, raise awareness of these concerns, and mobilise support. Social media debates spurred by hashtags like #BlackLivesMatter and #JusticeForGeorgeFloyd have attracted attention from around the world, challenged established power structures, and called for social transformation (Malecki, Keating and Safdar, 2021). Social media has also made it easier for knowledge to spread quickly to a large audience. The dissemination of news may be delayed by the editorial procedures and time restraints that traditional media organisations frequently face. Social media, on the other hand, provides for real-time updates, making it possible to quickly share important information during catastrophes and public health issues. Social media channels' immediate nature has been extremely helpful in delivering fast updates about COVID-19 instances, safety precautions, and vaccine programmes. People have been able to make well-informed decisions, adapt to changing conditions, and take the required safeguards to protect themselves and their communities because to this real-time information flow.

Social media's influence on public opinion, nevertheless, is not without drawbacks. The proliferation of false information and its ability to sway public opinion are among the major worries. On social media sites, false and misleading material concerning COVID-19 has become commonplace, including conspiracy theories, miraculous treatments, and incorrect numbers. This false information may cause uncertainty, worry, and even destructive actions. Social media businesses have put in place fact-checking procedures, algorithms that limit the exposure of deceptive content, and collaborations with trustworthy sources of information to address this problem. The development of echo chambers and filter bubbles on social media is another issue. Individuals may be exposed to material primarily that supports their pre-existing thoughts and opinions due to algorithms and user choices. This may exacerbate prejudices, obstruct critical thought, and reduce the variety of viewpoints. Social media users could thus become segregated in their own ideological spheres, fuelling polarisation and the spread of extremist perspectives. Additionally, social media's influence on information distribution goes beyond public opinion. More people now get their news from social media platforms than from conventional media sources. The dependability and quality of information have come under scrutiny as a result of this change in news consuming patterns. Fact-checking and verification procedures may not be able to keep up with the speed at which information flows on social media, causing false

information to proliferate before it can be refuted (Pulido et al., 2020). In order to manage the large quantity of information available on social media, it emphasises the significance of media literacy and critical thinking abilities. Social media significantly influenced how the COVID-19 epidemic was seen by the general public and how information was disseminated there. It has allowed the speedy spread of information, increased awareness of social concerns, and empowered people to share their thoughts. To guarantee that social media remains a trustworthy and responsible venue for public conversation and information exchange, issues like the proliferation of false information and the creation of echo chambers must be addressed.

During the COVID-19 epidemic, Arab social media platforms were extremely important for spreading information, influencing public opinion, and expressing feelings. Arab social media interactions have been analysed using sentiment analysis, which has revealed insights into the sentiments, emotions, and attitudes of the Arab populace about the epidemic and its effects on their life. Important conclusions have been drawn from studies on sentiment analysis in Arab social media during the outbreak. For example, AlTarrah et al.'s work from 2021 focuses on the sentiment analysis of Arabic tweets on COVID-19 in the Arab region. To classify tweets into good, negative, or neutral attitudes, the researchers used machine learning algorithms and natural language processing techniques. The survey discovered that Arab social media users showed a wide range of emotions, including dread, worry, irritation, solidarity, and hope (Alsayat, 2022). The differing opinions across nations and regions were a reflection of the particular difficulties and experiences that Arab communities had to deal with throughout the epidemic. A further research by Alqurashi et al. (2020) looked at sentiment analysis in talks on Arabic social media about public health initiatives and official reactions to the epidemic. The study found a range of opinions; some people had favourable feelings about government efforts like lockdowns and healthcare programmes, while others had negative feelings about perceived inefficiencies or a lack of transparency. The study made clear how crucial it is to take into account cultural quirks and contextual considerations when examining attitudes on Arab social media sites. During the epidemic, Arab social media users used sentiment analysis to get important insights into the worries, views, and experiences of Arab communities. It has clarified the sociocultural variables that affect how people express their emotions as well as the particular difficulties that Arab communities encounter. For instance, studies have emphasised feelings

about how lockdown procedures affect everyday living, financial difficulties, access to healthcare facilities, and false information spreading on social media sites.

Additionally, sentiment analysis has been useful in determining how the Arab public feels about certain COVID-19-related issues. Studies have looked at attitudes towards immunisation campaigns, adherence to preventative measures, assessments of government communication, and confidence in medical authority. Policymakers and public health professionals have been able to better address public concerns, debunk myths, and encourage behaviour change by adjusting their language and actions thanks to these findings. It is crucial to recognise the difficulties encountered while analyzing sentiment on Arab social media during the outbreak. The variety of Arabic dialects spoken in various Arab nations is one of the difficulties. The creation of specialised resources and techniques is necessary for reliable sentiment categorization since different dialects, colloquialisms, and regional phrases make sentiment analysis more difficult. The existence of social and cultural standards that affect how sentiments are expressed is another difficulty. Arab countries have a variety of cultural traditions, religious practises, and social standards that influence how opinions are publicly expressed. These cultural differences must be taken into account in sentiment analysis investigations to prevent misunderstanding or oversimplification of attitudes. Finally, sentiment analysis of Arab social media during the COVID-19 epidemic has given us important new understandings of the attitudes, sentiments, and feelings of Arab communities. Researchers have been able to capture the wide range of responses, worries, and experiences of Arab communities throughout the crisis by analyzing opinions posted on social media sites (Althagafi et al., 2021). In order to successfully address public concerns, enhance interventions, and promote public health initiatives, legislators, healthcare professionals, and communication methods have benefited from these findings. To ensure the accuracy and cultural relevance of sentiment analysis in Arab social media, however, issues linked to language variety and cultural subtleties must be taken into account.

In tasks involving sentiment analysis for different languages, including Arabic, and deep learning models have shown astounding performance. Due to the peculiar qualities of the language, such as its rich morphology, complicated syntax, and distinctive linguistic aspects, sentiment analysis in Arabic texts presents particular difficulties. Deep learning methods, on the other hand, have shown to be successful in extracting sentiment data from Arabic text and

reaching cutting-edge performance in sentiment classification tasks. The availability of labelled data is one of the key factors in sentiment analysis of Arabic text. Due to the dearth of publicly accessible annotated datasets for Arabic sentiment analysis, deep learning models frequently require substantial volumes of labelled data for training. However, initiatives have been undertaken to overcome this problem by developing specialised datasets for sentiment analysis in Arabic or by translating or modifying current resources from other languages. Deep learning architectures that are frequently utilised for sentiment analysis in Arabic text include convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs are appropriate for jobs requiring sentence-level sentiment categorization since they are proficient at identifying local patterns and relationships in text. CNNs may learn to extract pertinent characteristics and accurately capture the sentiment contained in a single phrase by training them to apply convolutional filters to particular sections of text. CNNs' hierarchical architectures enable them to capture several linguistic feature levels, including words, phrases, and sentence structures, which are essential for Arabic sentiment analysis. Arabic text may be modelled sequentially and long-term dependencies can be captured using RNNs, especially variations like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Understanding the contextual connections between words and sentences is a key component of sentiment analysis, and RNNs are excellent at capturing these dependencies by changing their hidden states depending on previous inputs at each step. RNNs are able to accurately capture the sentiment represented in lengthier texts, like reviews or social media postings, by learning from the sequential structure of Arabic language. Deep learning models for Arabic sentiment analysis have also used attention processes in them. By giving distinct words or phrases varying weights based on how important they are for sentiment classification, attention mechanisms enable the models to concentrate on the informative sections of the input. By doing so, the models are better able to accurately capture the most important information and perform better while doing sentiment analysis. Particularly helpful in catching minute nuances and tackling the complexity of sentiment expression in Arabic language are attention-based models.

Deep learning algorithms for sentiment analysis of Arabic text have also been investigated. The issue of minimal labelled data may be solved by pre-training models on large-scale datasets from comparable tasks or domains and then fine-tuning them on sentiment analysis tasks in Arabic. Transfer learning enables models to make use of the information and representations

learnt during the pre-training phase, improving sentiment analysis performance. Additionally, initiatives have been undertaken to provide specialised Arabic sentiment analysis tools and materials. These consist of domain-specific sentiment analysis models, sentiment-aware embedding, and sentiment lexicons. Taking into account the Arabic language's distinctive grammatical traits and cultural subtleties, these tools aid in capturing the sentiment-specific components of the language. However, there are still certain difficulties with sentiment analysis in Arabic text. Arabic is a very morphologically complicated language, and the existence of several dialects further makes things more difficult. To address problems like stemming, tokenization, and discretization, Arabic text-specific pre-processing and normalisation methods are needed. A problem with sentiment analysis is the lack of labelled data, particularly for applications that need fine-grained or domain-specific analysis. The creation and assessment of deep learning models are hampered by the lack of Arabic-specific tools and standards. Deep learning models have showed potential in tasks involving Arabic text sentiment analysis. These models can efficiently collect sentiment information and reach cutting-edge performance by utilising CNNs, RNNs, attention mechanisms, and transfer learning. The accuracy and application of deep learning models for sentiment analysis in Arabic text can be further improved by tackling the issues related to data availability, language-specific pre-processing, and domain-specific sentiment analysis.

The present study looked at how Arab populations responded to the COVID-19 pandemic on Twitter since the beginning of the outbreak in 2019. The purpose of the research is to collect and analyse data from both regular users and leaders posted on Twitter. This research study is centred on a model that has been designed to detect real news associated with the COVID-19 pandemic in Arabic Text taken from Twitter for Gulf countries. To begin with this research, we have made a comparison between the views of the general public and those of leaders with regards to Covid-19 after gathering the data.

1.2 Problem Statement

After examining the situation, many strategies were utilized for sentiment analysis; this research study concluded the following principal points which were taken into account while enacting the plan. The main goal was to consider the sentiment of the people in the COVID19 crisis. Data

mining techniques were used to secure a multilingual dataset. Assessments were performed on multiple sources to gain a broad understanding of the pandemic condition. Therefore, it is necessary to authenticate the details on social media, Natural Language Processing (NLP) was implemented with a range of methods to extract the lexical text information. Statistical evaluation was required to obtain data knowledge. Machine learning, deep learning, and ensemble learning schemes were also utilized for sentiment analysis. The model proposed in this section is intended to perform the procedure for sentiment analysis by using an Arabic tweets dataset.

1.3 Research Aim

The aim of this research is to investigate the sentiment of Gulf opinion leaders and the general public on Twitter with regard to COVID-19 in the Arabic language. This study aims to develop a deep learning model to detect real news related to the pandemic and analyse the sentiments expressed in the tweets.

1.4 Research Questions

The following research questions have been guide in this study:

- What are the views of Gulf opinion leaders and the general public on Twitter regarding COVID-19 in the Arabic language?
- How can a deep learning model be used to detect real news related to the pandemic in Arabic text on Twitter?
- What are the sentiments expressed by Gulf opinion leaders and the general public regarding COVID-19 on Twitter?

1.5 Research Objectives

The following research objectives have been pursued to achieve the research aim and answer the research questions:

- To analyse the views from Gulf opinion leaders and the general public on Twitter regarding COVID-19 in the Arabic language.
- To identify a deep learning model to detect real news related to the pandemic in Arabic text on Twitter.
- To evaluate the performance of the deep learning model in detecting real news related to COVID-19 on Twitter.
- To analyse the sentiments expressed by Gulf opinion leaders and the general public regarding COVID-19 on Twitter.

1.6 Research Significance

This study is significant in several ways. First, it contributes to our understanding of how Gulf opinion leaders and the general public are responding to COVID-19 on Twitter. Second, the study is evaluating an appropriate deep learning model to detect real news related to the pandemic in Arabic text on Twitter, which can help in identifying and combating misinformation related to the pandemic. Third, the study also give its contribution to the field of sentiment analysis by analyzing the sentiments expressed by Gulf opinion leaders and the general public regarding COVID-19 on Twitter. Fourth, the study have provided insights into the use of deep learning models in sentiment analysis and news detection in the Arabic language. Due to the volume of information published on the site and the presence of false information and fake news, it can be difficult to identify actual news in Arabic text on Twitter. However, a number of strategies have been devised to address this problem and guarantee the veracity of news being shared on Twitter. These strategies make use of a variety of methods, including data analysis, machine learning, and natural language processing (NLP). To find language patterns and signs of actual news, lexical analysis examines the lexical content of tweets. This method focuses on identifying words, phrases, and linguistic characteristics that are connected to reputable and trustworthy news sources. Lexical analysis methods can assist distinguish between factual tweets from reliable sources and possibly fraudulent or misleading information. Sentiment analysis is an effective method for identifying authentic news on Twitter. It is possible to spot trends that point to the veracity of news by looking at the mood conveyed in

tweets. While disinformation or false news may contain biased or exaggerated attitude, genuine news pieces typically convey facts in a neutral or impartial manner. Algorithms for sentiment analysis can be used to find tweets that differ from the regular sentiment patterns seen in authentic news sources. Techniques for evaluating the trustworthiness of news sources referenced in tweets are called credibility evaluation techniques. In this method, the credibility, dependability, and trustworthiness of the news source or the news provider are evaluated. It takes into account elements including the source's track record for factual reporting, verification procedures, and adherence to journalistic norms. The validity of the news being posted on Twitter may be ascertained by evaluating the reliability of news sources. This type of study focuses on evaluating the authority and trustworthiness of Twitter users who share news. This method evaluates the effect and impact of a user's tweets by considering variables including the number of followers, retweets, likes, and responses. Real news is more likely to be shared by people who have a history of offering accurate information and receive a lot of engagement from other users. Prioritising tweets from trustworthy people or organisations can help eliminate untrustworthy sources by analyzing user impact and interaction. Verification and fact-checking are essential for spotting actual news on Twitter. Fact-checkers actively confirm tweets' claims by performing in-depth research and consulting reliable sources. Fact-checking organisations work with social media platforms to identify or flag tweets that include false information or to respond to false claims with verifiable information. The veracity of news reported on Twitter may be confirmed by including fact-checking systems and working with reliable fact-checking organisations.

Machine learning and deep learning models have demonstrated potential in the detection of authentic news in Arabic language on Twitter. Large datasets of verified news stories and false information may be used to train these algorithms so they can discover patterns and traits that tell the two apart. It is now feasible to categorise tweets as actual news or false information based on learnt characteristics and patterns by utilising machine learning methods like support vector machines, random forests, or deep learning architectures like recurrent neural networks (RNNs) or transformer models. To increase the precision of identifying true news on Twitter, hybrid approaches integrate many techniques and procedures. These techniques take use of each method's capabilities by combining lexical analysis, sentiment analysis, credibility evaluation, user impact analysis, and machine learning models to provide more trustworthy findings.

Combining several methods lessens their individual drawbacks and offers a more thorough evaluation of the veracity of news posts on Twitter. The multifaceted strategy that integrates lexical analysis, sentiment analysis, credibility evaluation, user influence analysis, fact-checking, and machine learning models is needed to identify true news in Arabic language on Twitter. Utilising these strategies makes it feasible to weed out false information and encourage the spread of accurate and trustworthy news on Twitter, resulting in a better informed public conversation.

Sentiment analysis has become an important method for analyzing people's thoughts, feelings, and attitudes during this crisis as a result of the substantial effects the COVID-19 epidemic has had on communities throughout the world. To better understand public opinion, track changes over time, and pinpoint major themes and concerns, researchers and analysts have carried out various studies on sentiment analysis in relation to the epidemic. Analyzing emotions posted on social media sites has been a focus of sentiment analysis studies during the COVID-19 epidemic. People now often use social media sites like Twitter, Facebook, and Instagram to express their opinions, worries, and personal experiences with the epidemic (de Las Heras-Pedrosa, Sánchez-Núñez and Peláez, 2020). The public's reaction to the crisis has been better understood by scholars thanks to their analysis of the views expressed on these platforms. For instance, Zhang et al.'s (2020) study used tweets about COVID-19 to gauge public opinion during the pandemic's early phases. The study classified tweets into favourable, negative, or neutral attitudes using machine learning techniques. The findings showed a range of emotions, with fear, anxiety, and anger dominating the negative ones. The survey also discovered that opinions changed over time and in different geographical areas as the epidemic progressed. Liang et al.'s (2020) sentiment analysis of internet news stories on COVID-19 was the topic of another research. To analyse the feelings represented in the news items, the researchers combined lexicon-based and machine learning methodologies. The results revealed the predominately negative feeling, with the most often indicated emotions being fear, despair, and rage. The survey also highlighted certain issues, such as government regulations, healthcare systems, and financial consequences that led to bad feelings. Studies on sentiment analysis have looked at the opinions expressed in online forums, blogs, and other online platforms in addition to social media and news items. These studies have given us invaluable information on certain groups throughout the pandemic,

including as healthcare professionals, decision-makers, or those with pre-existing medical issues.

Sentiment analysis has also been used to examine attitudes towards particular COVID-19-related issues. Studies have examined attitudes regarding the usage of face masks, the COVID-19 vaccination, or the efficacy of public health interventions, for instance. Policymakers and healthcare professionals may modify their messaging and actions to meet public concerns and encourage adherence to advised recommendations by being aware of how the public feels about these issues. It is important to note that sentiment analysis in the context of the COVID-19 epidemic has its own difficulties and restrictions. The pandemic's quick evolution and the feelings that go along with it provide one of the main difficulties (Laxminarayan et al., 2020). As new information becomes available, regulations and procedures are revised, or as the seriousness of the issue changes, feelings might shift. Therefore, to capture these dynamic changes, sentiment analysis studies must take into account the temporal component and follow sentiments through time. Another difficulty is the possibility for false information and rumours on social media sites, which might sway opinions. For precise insights to be gained, it is essential to distinguish between true feelings and feelings fuelled by false information. Researchers have created methods to identify and eliminate erroneous information, such as using user credibility measures or fact-checking sources. Sentiment research during the COVID-19 epidemic has given us important insights into how the general public feels about different facets of the problem (Barkur and Kamath, 2020). Researchers have been able to record the public's reaction to the epidemic, track changes over time, and pinpoint major issues and themes by examining views expressed in social media, news stories, and internet forums. To guarantee the accuracy and trustworthiness of sentiment analysis research, however, issues including the dynamic nature of sentiments and the existence of disinformation must be addressed.

1.7 Dissertation Structure

The dissertation is following the structure;

- Chapter 1 introduces the topic of the research, which is focused on the response of Arab populations to the COVID-19 pandemic on Twitter, since the outbreak in 2019. The

chapter provides a background and context for the research, problem statement, research aim, research questions, research objectives and research significance. The chapter concludes with a summary of the contents of the subsequent chapters.

- Chapter 2 presents a comprehensive review of the literature related to the research topic. The chapter includes an introduction to the COVID-19 pandemic in the Gulf region, followed by a discussion on sentiment analysis, including its definition and methods. Deep learning approaches for sentiment analysis, Arabic language processing, and social media and sentiment analysis are also discussed. The chapter concludes with a review of sentiment analysis on Twitter.
- Chapter 3 describes the methodology used in the research. The chapter includes an introduction to the research design, followed by a discussion of the data collection and pre-processing methods used. The chapter then describes the design and implementation of the deep learning model for sentiment analysis. The evaluation methodology used to assess the performance of the model is also discussed. The chapter concludes with a summary of the methodology used.
- Chapter 4 presents the results of the research and provides a discussion of the findings. The chapter includes an introduction to the data analysis and results, followed by a presentation of the sentiment analysis results. The evaluation results of the model are also discussed. The chapter then provides a detailed discussion of the results and their implications. The chapter concludes with a summary of the key findings.
- Chapter 5 presents the conclusions drawn from the research and provides suggestions for future work. The chapter includes a summary of the research aim, research questions, research objectives, and research significance. The key findings are then discussed, followed by an overview of the contributions and implications of the research. The limitations of the research are also discussed, and recommendations for future work are presented. The chapter concludes with a summary of the research and its implications.

CHAPTER 2: LITERATURE REVIEW AND RELATED WORK

2.1 Introduction to the Chapter

The literature review is an essential component of the research, as it provides a comprehensive understanding of the research area, and helps to identify research gaps and future research directions. In this chapter, the research topic is situated within the broader context of sentiment analysis, including its definition, methods, and applications. The chapter explores the current state of research on sentiment analysis in the context of social media, specifically on Twitter. Moreover, the chapter investigates deep learning approaches for sentiment analysis, including techniques for Arabic language processing, which are relevant for the proposed study. The literature review was conducted by searching electronic databases, including published articles and books, to identify relevant studies that address the research area. The chapter provides an overview of the current state of research in the field, identifies research gaps, and informs the research methodology and approach for this study.

2.2 Sentiment Analysis Perception Related to COVID-19

COVID-19 pandemic has significantly impacted the world, causing physical and mental distress in individuals. In recent years, sentiment analysis has emerged as a crucial tool for understanding people's emotions and opinions related to events and situations, therefore; the following sections are examining the sentiment analysis studies conducted to understand people's perceptions related to COVID-19 with various methods and approaches.

2.3 Sentiment Analysis from Social Media

Social media has become a popular platform for people to express their views and emotions about the pandemic. Many studies have used sentiment analysis on social media platforms such as Twitter and Facebook to analyse people's perceptions of COVID-19. For instance, a study conducted by Hussein and colleagues (2021) used sentiment analysis on Twitter to investigate people's emotions related to COVID-19 in Saudi Arabia. The study found that the majority of the tweets expressed negative sentiments, indicating the high level of anxiety and fear among

people. Another study by Chakraborty and colleagues (2020) analysed Twitter data related to COVID-19 to understand the public's perception of the pandemic in India. The study used machine learning algorithms to classify tweets into positive, negative, and neutral sentiments. The findings of study revealed that the majority of the tweets expressed negative sentiments, primarily fear, and anger.

Recently, the ongoing pandemic has been one of the most discussed topics globally. To further the progress of research on this topic, Alharbi, Kalkatawi, and Taileb (2021) conducted a study to analyse the depression symptoms of Arabs during COVID-19 using a Recurrent Neural Networks (RNN) algorithm. By analyzing the tweets of Arab women, the study concluded that RNN had the highest accuracy of 72% when compared to other existing models (Oussous et al., 2020). Further, a study by Gwad, Ismael, and Gültepe (2020) adopted machine learning and deep learning techniques, particularly the Long Short-Term Memory (LSTM) deep learning algorithm and CNN (Convolution Neural Network) are commonly used to recognize and classify the sentiment of people from their tweets about pandemic.

It is impossible to exaggerate the value of social media in crisis communication, particularly in light of the COVID-19 epidemic. Social media sites have grown to be effective tools for sharing information, giving updates, and interacting with the public in emergency situations. Social media platforms have revolutionised the way information is exchanged and consumed, and because of their extensive reach, real-time communication capacities, and user-friendly interfaces, they are crucial in times of international health crises. The capacity of social media to swiftly reach a big audience is one of its primary advantages in crisis communication. The ability for health organisations and authorities to quickly broadcast important information is unparalleled because to the billions of active users on platforms like Twitter, Facebook, Instagram, and WhatsApp. Health organisations like the World Health Organisation (WHO) and the Centres for Disease Control and preventative (CDC) have used social media throughout the COVID-19 pandemic to communicate information on the changing situation, preventative and control recommendations, and significant announcements (Abbas et al., 2021). Social media enables for instant connection and involvement due to its real-time nature. Timely information is essential during a crisis as it aids in addressing public concerns, putting to rest rumours, and offering direction. Health officials may interact directly with the public through social media channels, answering inquiries, dispelling myths, and quickly resolving issues. Through direct

interaction, health organisations and the public may work together to increase openness and develop confidence.

Additionally, social media provides a user-friendly interface that makes it simple to share and consume information. People may quickly and easily get news, updates, and recommendations from reliable sources. People may easily spread vital information outside of official channels by sharing posts, videos, and links with their networks. By doing so, people can amp up crucial messages. This user-driven information sharing may encourage a greater uptake of preventative measures and community involvement in public health initiatives. Peer-to-peer contact and social support networks are also made possible by social media platforms in times of disaster. People have used social media during the COVID-19 epidemic to discuss their experiences, get advice, and provide support to one another (Malecki, Keating and Safdar, 2021). People can connect, exchange resources, and receive emotional support during trying times thanks to platforms like Facebook groups, forums, and Twitter conversations. These groups have been crucial in building a feeling of community among those impacted by the epidemic, minimising social isolation, and encouraging resilience. However, it's critical to recognise the difficulties and constraints social media face in crisis communication. People may struggle to discern between reliable information and rumours or fraudulent claims due to the volume of information available on social media. On social media sites, false information and conspiracy theories about COVID-19 have quickly propagated, leading to misunderstandings and perhaps hazardous behaviours. Social media's ability to spread disinformation quickly can undermine attempts to improve public health and exacerbate the situation.

Social media platforms and health authorities have taken action to counteract the transmission of false information and promote factual information in order to solve these issues. Social media platforms have put standards in place to identify and delete anything that is inaccurate or misleading about COVID-19 (Visca et al., 2021). To provide trustworthy sources and advance factual information, they have also worked with fact-checking agencies and health authorities. Public health programmes have been started to equip social media users with media literacy and critical thinking abilities, enabling them to check material before spreading it. Social media sites have evolved into crucial instruments for communicating amid crises, as during the COVID-19 epidemic ((Abbas et al., 2021). The way information is exchanged and consumed has changed dramatically as a result of their capacity to instantly reach a huge audience, enable real-time

conversation, and stimulate peer-to-peer assistance. To make sure that social media remains a dependable and efficient conduit for crisis communication, it is crucial to address the problems caused by disinformation and encourage media literacy.

During the COVID-19 epidemic, social media use in the Arab world increased significantly and developed into a vital instrument for communication for people, groups, and organisations. Due to the widespread usage of the internet and the rising number of social media users in the Arab world, these platforms are frequently used for communication, contact, and engagement with the public during crises. The demand for quick and accurate information is one of the main factors driving the surge in social media usage in the Arab world during the epidemic. Arab people rely on social media sites like Facebook, Twitter, and WhatsApp to stay up to speed on COVID-19 cases, cures, and official directives. People may keep updated about the quickly changing circumstances by using these sites as a source of real-time news. Utilising social media platforms, health organisations, governmental organisations, and media outlets provide official information and stop the spread of false information. During the epidemic, social media significantly contributed to the development of community participation and solidarity in the Arab world (Ghounane, 2020). People have organised community efforts using tools like Facebook groups, Instagram stories, and Twitter threads to share personal experiences and solicit support. This feeling of community has given people the tools they need to face the difficulties the epidemic has brought about by giving them a forum for emotional support, resource sharing, and group action. Social media has aided in the development of online communities that have banded together to solve a variety of COVID-19-related concerns, including setting up online support groups for mental health and distributing food and supplies to vulnerable populations (Visca et al., 2021). Social media platforms have been crucial in increasing awareness and boosting public health initiatives in the Arab world, in addition to information exchange and community participation. Celebrities, public figures, and influencers have all utilised their social media platforms to convey correct information, support responsible behaviour, and support preventive actions. This influencer-driven strategy has been successful in reaching sizable audiences and spreading important COVID-19 themes. Innovative initiatives that attempt to inform, inspire, and engage people in adopting healthy behaviours have been produced as a consequence of partnerships between health organisations and social media celebrities.

Additionally, social media has given Arab people and groups a forum to communicate their worries, annoyances, and opinions on the epidemic. On numerous social media platforms, people have engaged in online conversations and debates to express their opinions on government actions, political choices, and the overall impact of COVID-19. This online forum for public dialogue has greatly contributed to the formation of public opinion, the influencing of public policies, and the accountability of authorities. It is crucial to recognise that using social media during the epidemic in the Arab world is not without difficulties. The proliferation of false information and fake news has been a major problem, since it may cause confusion and even injury. On social media platforms, rumours, conspiracies, and unsubstantiated information about COVID-19 have been spread, adding to the infodemic. As a result, social media corporations and health organisations have introduced fact-checking procedures, labelled erroneous content, and promoted trustworthy sources of information in an effort to counteract disinformation. Concerns about data security and privacy on social media sites are also present (Kaya, 2020). An awareness of privacy settings, data protection, and the possible abuse of personal data is necessary when people share personal information and participate in online debates about the epidemic. Arab social media users must be aware of privacy regulations, take caution when disclosing personal information, and remain up to speed on security precautions (Visca et al., 2021). Social media use has significantly increased and developed into a crucial communication tool in the Arab world during the COVID-19 epidemic. These platforms have made current information accessible, promoted community involvement, increased awareness, and given people a forum for free speech. To guarantee that social media remains a dependable and useful tool in times of crisis, issues like the propagation of false information and privacy concerns must be resolved.

A computational method called sentiment analysis, commonly referred to as opinion mining, analyses text data to ascertain the sentiment or emotional tone portrayed within the text. It seeks to comprehend and interpret the feelings, attitudes, and views of people towards a certain issue, good, service, or event. Sentiment analysis is a technique used to separate out subjective information from textual data and categorise it as either good, negative, or neutral. Understanding and using the power of text data, which is now more prevalent than ever in the digital era, requires sentiment analysis. As social media platforms, online reviews, blogs, and news stories have proliferated, so has the amount of user-generated material that may be

analysed. Organisations and individuals may learn a lot about public opinion, consumer feedback, brand reputation, market trends, and other things by using sentiment analysis tools. For businesses looking to better understand client sentiment and adjust their products or services appropriately, sentiment analysis has proven to be a priceless tool. Businesses may better understand customer happiness, pinpoint frequent pain areas, and make data-driven choices to improve customer experience by analyzing customer reviews, social media posts, and other user input. Businesses may react swiftly to shifting customer preferences by using sentiment research to spot new trends and sentiment shifts. Organisations may track and examine online conversations in real-time using sentiment analysis in the field of social media monitoring. Businesses may determine how the public feels about their brand, goods, or campaigns by monitoring social media mentions and sentiment ratings. This data may be used to manage online reputation, find influencers or brand champions, and evaluate the effectiveness of marketing activities (Zavattaro, French and Mohanty, 2015). Additionally useful in the sphere of market research is sentiment analysis. Given that they rely on self-reported opinions, which can be skewed or impacted by a number of circumstances, traditional survey-based procedures may have drawbacks. Researchers may use sentiment analysis to dig deeper into customer sentiment and preferences by examining massive amounts of text data from sources like online comments, forum threads, and social media postings. This helps firms to decide on product development, marketing plans, and market positioning with knowledge.

Additionally, sentiment analysis has political applications that help scholars and decision-makers assess how the public feels about political figures, proposals, or societal concerns. Sentiment analysis may shed light on the dynamics of public opinion, sentiment polarisation, and the effects of political campaigns by examining social media conversations and news stories. Political organisations may use this information to improve their messaging, pinpoint the most pressing concerns, and adjust their plans as necessary. Recent developments in Natural Language Processing (NLP) and machine learning methods have significantly improved sentiment analysis. In addition to identifying sentiment, NLP algorithms are now able to comprehend contextual cues, sarcasm, irony, and other types of sentiment expressions (Serrano-Guerrero et al., 2015). This has increased the precision and dependability of sentiment analysis, enabling more complex insights into the thoughts and feelings of people. Finally, sentiment analysis is an effective method that enables businesses and people to derive significant

knowledge from textual data. Sentiment analysis offers a data-driven method for identifying the underlying emotions, attitudes, and views represented in text, whether the goal is to comprehend customer sentiment, monitor business reputation, or study public opinion. With the proliferation of digital material, sentiment analysis is still essential for comprehending and maximising the potential of textual data across a range of applications.

2.4 Sentiment Analysis from News Articles and Online Reviews

In addition to social media, sentiment analysis has been used to analyze news articles related to COVID-19. A study conducted by Guo and colleagues (2021) analysed news articles related to COVID-19 in China using a lexicon-based approach. The study found that the majority of the articles expressed negative sentiments, primarily fear, and sadness. The study concluded that the negative sentiment of news articles related to COVID-19 could impact people's mental health.

On the other hand, online reviews have become an essential source for understanding people's opinions and perceptions of products and services. A study conducted by Lewis, Tabassum and Bibhuti (2021) used sentiment analysis on online reviews related to COVID-19 products such as masks and hand sanitizers. The study found that the majority of the reviews expressed positive sentiments, indicating that people trust these products to protect themselves from COVID-19. Hence, the studies reviewed above indicated that sentiment analysis can provide valuable insights into people's perceptions related to COVID-19. The majority of the studies found that people express negative sentiments, primarily fear and anxiety related to COVID-19. These negative sentiments expressed through social media and news articles could impact people's mental health. However, online reviews related to COVID-19 products generally express positive sentiments, indicating people's trust in these products to protect themselves from the virus. Overall, sentiment analysis can be a valuable tool for understanding people's emotions and opinions related to COVID-19, which could help health authorities and policymakers make informed decisions.

2.5 Deep Learning Approaches for Arabic Sentiment Analysis

There are several kinds of deep learning approaches for analyzing the sentiment analysis and various studies have done on these approaches. Some of the most significant deep learning approaches are mentioned below with the reference of studies.

Opinion mining, another name for sentiment analysis, uses a variety of methods and strategies to extract subjective data and categorise it. These methods and strategies include both conventional rule-based strategies and more sophisticated machine learning algorithms. The approach selected is determined by the unique needs of the analysis and the resources at hand. Lexicon-based analysis is one of the conventional methods used in sentiment analysis (Thakkar and Patel, 2015). Words or phrases linked to different levels of feeling can be found in lexicons or dictionaries. Each word or phrase is given a sentiment score that indicates whether it is neutral, positive, or negative. In lexicon-based analysis, words or phrases from the text are compared to lexicon entries, and the matched sentiments are then used to determine an overall sentiment score. Although this method is rather straightforward and effective, it may be difficult to handle sarcasm, irony, or terminology peculiar to a certain field since it lacks contextual awareness. A different strategy is machine learning-based sentiment analysis, which entails building a model from scratch on a labelled dataset to discover trends and connections between text and sentiment (Thakkar and Patel, 2015). For sentiment classification, supervised learning methods like Support Vector Machines (SVM), Naive Bayes, or neural networks are frequently employed. As training data, these algorithms require a labelled dataset with sentences that have already been categorized. In order to categorise unknown text, the model generalises the patterns it learns from these instances. Machine learning-based methods are capable of handling complicated patterns, capturing contextual data, and adjusting to various domains. However, they may be computationally costly and need a large amount of labelled training data. Deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have become more common in sentiment analysis in recent years. RNNs are ideally suited for analyzing textual data since they can capture sequential information (Jain and Dandannavar, 2016). They are proficient in modelling the relationships between words in a phrase and accumulating long-term contextual data. On the other hand, CNNs are good at identifying regional trends and characteristics in text. There is no need for manually created

lexicons or features because these deep learning models can automatically learn the representations and features from the text. They have demonstrated promising outcomes in jobs involving sentiment analysis, particularly when it comes to collecting nuanced feelings and managing huge datasets. Deep learning models, however, often need a lot of training data and computer power.

Sentiment analysis has also utilised unsupervised learning techniques in addition to supervised learning. Without the use of pre-labeled samples, unsupervised approaches look for patterns or clusters in text data. Similar texts can be grouped together by clustering algorithms, such as K-means or hierarchical clustering, depending on how similar they are. When there is a lack of or access to labelled training data, unsupervised procedures might be helpful. However, because they significantly rely on the quality of the initial data representation or feature engineering, they might not attain the same degree of accuracy as supervised learning systems. In sentiment analysis, hybrid methods that combine several methodologies have also been investigated. A hybrid strategy may, for instance, employ lexicon-based techniques for feature extraction and machine learning algorithms for sentiment categorization. This can combine the benefits of both strategies and boost performance as a whole. Sentiment analysis uses a variety of methods and strategies to identify and categorise the emotions expressed in text. Lexicon-based analysis offers a quick and effective way, although it might not take into account context (Thakkar and Patel, 2015). Deep learning models and other machine learning-based techniques are capable of capturing complicated patterns and contextual data, but they also need processing power and labelled training data. When labelled data is scarce, unsupervised learning techniques provide alternatives, however they might not be as accurate as supervised learning. In order to maximise the benefits of each methodology, hybrid methods combine several of them. The precise needs of the sentiment analysis task and the resources at hand determine the approach to use.

Sentiment analysis relies heavily on Natural Language Processing (NLP), which makes it possible to automatically comprehend and interpret human language in textual data. By offering strong tools and strategies for extracting and analyzing sentiment-related information from text, NLP approaches have substantially advanced sentiment analysis. Text preparation is one of the main ways that NLP is used in sentiment analysis. Text data frequently has to go through pre-treatment methods to clean up and normalise the text before sentiment analysis is performed. Tokenization, the process of breaking up text into individual words or tokens, the removal of

punctuation and special characters, the conversion of text to lowercase, and the management of stopwords (common words like "the," "is," etc.) are some of the responsibilities involved in this. To carry out these preparation activities, NLP approaches offer effective algorithms and tools, guaranteeing that the text is in an appropriate format for sentiment analysis. Feature extraction is a vital NLP technique for sentiment analysis. In order to extract the pertinent information from text that expresses sentiment, features are crucial. Bag-of-words (BoW), n-grams, and word embedding are only a few of the feature extraction approaches offered by NLP techniques. When text is represented using the BoW method, it is turned into a matrix of word frequencies, whereas n-grams preserve the order of neighbouring words. Words are represented as dense vector representations in word embedding, such Word2Vec or GloVe, which capture the semantic links between words. With the help of these feature extraction methods, it is possible to convert unstructured text into numerical representations that can be fed into sentiment analysis models (Parmar et al., 2018). Additionally, NLP methods are used in sentiment analysis to classify sentiment. Sentiment classification using NLP techniques and models may be done after the pre-processing and feature extraction of the text data. In jobs requiring sentiment categorization, supervised machine learning methods like Support Vector Machines (SVM), Naive Bayes, or Neural Networks are frequently employed. These algorithms generalise patterns learned from labelled training data to identify the emotion of unseen text. To accurately predict sentiment, NLP-based machine learning models may extract the context, syntactic patterns, and semantic meaning from the text.

Deep learning models and other sophisticated NLP approaches are useful for sentiment analysis as well. Convolutional and recurrent neural networks have demonstrated outstanding performance in sentiment analysis tasks. RNNs can recognise complicated sentiment patterns because of their capacity to represent sequential information and long-term relationships in the text. On the other hand, CNNs are proficient in identifying regional traits and trends in text, which helps with sentiment categorization. By automatically deriving representations and features from text input, these deep learning models take use of NLP's capability and eliminate the need for human feature engineering. By making it possible to analyse sentiment in several languages, NLP also plays a significant part in sentiment analysis. The use of NLP techniques has made it possible to process and analyse sentiment in multilingual text in languages other than English. Sentiment analysis has also grown beyond English to include other languages.

This involves the availability of language-specific sentiment lexicons or resources, as well as language-specific tokenization, stemming, and stopword removal (Wankhade, Rao and Kulkarni, 2020). As a result of the tools and methods it offers for text pre-processing, feature extraction, sentiment classification, and multilingual analysis, NLP significantly contributes to sentiment analysis. It is feasible to extract sentiment-related information and analyse sentiments at scale thanks to NLP, which enables the automatic comprehension and interpretation of human language in textual data. The creation of more precise and effective sentiment analysis models has greatly benefited from advances in NLP, enabling companies and organisations to get insightful information from text data and comprehend public sentiment.

2.5.1 Convolutional Neural Networks (CNN):

Although Convolutional Neural Networks (CNNs) are primarily used for image and video analysis, they have also proven to be effective for natural language processing (NLP) tasks such as sentiment analysis (Tsao et al., 2021). Typically, a CNN consists of one or more convolutional layers that are followed by fully connected layers. The convolutional layer applies a filter to the input data, typically an image or a sequence of word embedding's in NLP tasks. The filter moves across the input data, applying a dot product at each position, producing a feature map (Albahli, 2022). The feature map captures the presence of certain features in the input data, such as edges or patterns. According to the study of Radwan (2020), the fully connected layers receive the output of the convolutional layers and perform classification or regression tasks. The fully connected layers are responsible for learning the high-level features from the low-level features extracted by the convolutional layers. The final layer produces the output, which can be a single value or a vector of values.

The model under CNNs are trained using back propagation, a process that adjusts the weights of the network to minimize the risk between input and output. The weights of the convolutional layers are learned by gradient descent, a process that iteratively updates the weights to minimize the loss function (Rengasamy et al., 2020). A study by Ombabi, Ouarda and Alimi (2020) used CNN for Arabic sentiment analysis. The study used a pre-trained Arabic word embedding to represent the text and applied a CNN model to classify the sentiment. The model achieved an accuracy of 88.2%.

This type of networks have several advantages over other neural networks. They can learn the spatial and temporal dependencies between the input data, making them suitable for image and video analysis (Vijayalakshmi et al., 2021). In NLP tasks, CNNs can learn the local patterns and relationships between the words in the input data, making them suitable for sentiment analysis. Moreover, CNNs are computationally efficient and making themselves suitable for real-time applications.

2.5.2 Recurrent Neural Networks (RNN):

Recurrent Neural Networks (RNN) are often utilized in natural language processing (NLP) tasks such as sentiment analysis, speech recognition, and language modelling. Unlike feed forward neural networks, RNNs can handle sequential data through feedback connections that allow information to persist. In GAO et al.'s (2020) study, RNNs are composed of a hidden state that is updated at each time step based on the input at that time step and the previous hidden state. Typically, a vector representation, such as a word embedding, is used to represent the input at each time step. The output at each time step can be a single value or a vector of values, depending on the task at hand. Chintalapudi, Battineni and Amenta (2021) state that Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber in 1997, are the most widely used type of recurrent neural network (RNN) for natural language processing (NLP) tasks due to their ability to capture long-term dependencies in input data. LSTMs use a gating mechanism that allows them to selectively remember or forget information from previous time steps. The gating mechanism comprises three gates: the input gate, which decides how much new information should be added to the current hidden state; the forget gate, which determines how much of the previous hidden state should be forgotten; and the output gate, which decides how much of the current hidden state should be used to produce the output.

The RNNs are trained using back propagation through time (BPTT), which is a variant of back propagation that takes into account the feedback connections in the network. During training, the network tries to reduce the error among the predicted output and the actual output by using gradient descent. The RNNs have several advantages over other neural networks. They can handle sequential data of varying length, making them suitable for NLP tasks. Moreover, Vijay et al. (2020) suggested that RNNs can learn the temporal dependencies between the input data, making them suitable for sentiment analysis. However, RNNs also have some limitations. They

can suffer from the vanishing gradient problem, which occurs when the gradients become too small during back propagation, making it difficult to learn long-term dependencies. This problem has been addressed by LSTMs and other variants of RNNs such as Gated Recurrent Units (GRUs). These networks are type of neural network that can capture sequential information. A study by Setyanto et al. (2022) used RNNs for Arabic sentiment analysis and the model achieved an accuracy of 81.36%. The study used a long short-term memory (LSTM) RNN model to classify the sentiment.

2.5.3 Attention-Based Neural Networks:

Recent studies have demonstrated the efficacy of attention-based neural networks in enhancing the accuracy of sentiment analysis models. These types of neural networks have gained significant attention in the last few years due to their ability to boost the performance of sequence modeling tasks, including sentiment analysis, machine translation, and speech recognition (Usama et al., 2020). They are designed to concentrate on specific parts of the input sequence when processing each element of the output sequence, which enables them to effectively capture the relevant information required for accurate sentiment analysis. This selective focus is achieved by incorporating an attention mechanism into the neural network. The attention mechanism is responsible for assigning a weight to each element of the input sequence based on its relevance to the current output element being processed. There are different types of attention mechanisms that have been proposed in the literature, including additive attention, dot-product attention, and multiplicative attention.

The ABNNs have been applied to various NLP tasks, including sentiment analysis. For example, Attention-based models for sentiment analysis have gained significant attention in recent years due to their effectiveness in achieving state-of-the-art results on benchmark datasets. For instance, Ayetiran (2022) proposed an attention-based model that uses a convolutional neural network (CNN) to extract features from the input sequence and an attention mechanism to selectively focus on relevant features during the processing of each output element. Similarly, Basiri et al. (2021) proposed an attention-based model that uses a bidirectional LSTM (BiLSTM) to process the input sequence and selectively focuses on relevant parts of the input sequence using an attention mechanism. ABNNs have numerous advantages over traditional neural networks, as revealed by the study of Butt et al. (2021). They can handle variable-length

input sequences and selectively focus on relevant parts of the input sequence, making them ideal for sentiment analysis. However, they also have some limitations, such as being computationally expensive and requiring a considerable amount of labeled data to achieve good performance. To address these limitations, Haddad et al. (2020) utilized a self-attention mechanism in an attention-based neural network for Arabic sentiment analysis, achieving an accuracy of 88.73%.

2.5.4 Transformer-Based Models:

Transformers have emerged as the leading approach for various NLP tasks, particularly sentiment analysis. They are a neural network architecture that has gained significant usage in natural language processing tasks, including sentiment analysis. Vaswani and colleagues introduced the transformer architecture in 2017, which has now become a popular choice for many NLP tasks due to its capability of efficiently capturing long-range dependencies in sequential data. As per Antoun, Baly, and Hajj (2020), transformers are based on the attention mechanism, enabling the model to selectively focus on distinct parts of the input sequence. However, unlike traditional attention-based models, transformers use self-attention, which means that the model can attend to all the elements in the input sequence at the same time.

The transformer architecture comprises of an encoder and decoder, where the encoder processes the input sequence and creates a representation that can be utilized by the decoder to generate the output sequence. In contrast, the decoder generates the output sequence based on the representation produced by the encoder. The Bidirectional Encoder Representations from Transformers (BERT) model is a well-known transformer-based model that has been pre-trained on a vast corpus of text using an unsupervised learning approach, as demonstrated by Mostafa et al. (2021). During the pre-training phase, BERT accomplishes two tasks, namely masked language modeling and next sentence prediction. A study by Rai et al. (2022) used a transformer-based model called BERT for Arabic sentiment analysis. The study used pre-trained BERT models on Arabic text and fine-tuned the models for sentiment analysis. The model achieved an accuracy of 95.36%.

The task of masked language modeling involves masking words in an input sequence and training the model to predict the masked words based on the context provided by the other words in the sequence. Another task called next sentence prediction involves training the model to predict whether two input sequences are consecutive. After completing the pre-training phase,

the BERT model can be fine-tuned for a specific NLP task such as sentiment analysis. Fine-tuning involves training the model on a smaller labeled dataset and adjusting its weights to improve its performance on that task. Many studies have demonstrated that transformer-based models, including BERT, can achieve state-of-the-art results on sentiment analysis tasks. For instance, Liang et al. (2022) and Al-Twairish et al. (2021) proposed BERT-based models for Chinese and Arabic sentiment analysis, respectively, and achieved state-of-the-art performance on benchmark datasets. Precisely, transformer-based models are powerful tools for NLP tasks, especially sentiment analysis. They can efficiently capture long-range dependencies in sequential data and have proven to be highly effective in many benchmark datasets. However, they require a large amount of computational resources and can be challenging to train and deploy in real-world settings.

2.6 Sentiment Analysis in the Context of COVID-19

During the COVID-19 epidemic, sentiment analysis has shown to be a useful method for gauging public attitude and opinion. However, sentiment analysis has its difficulties and limitations just like any other analytical strategy. When doing sentiment analysis on COVID-19 speech, there are three major difficulties that academics and practitioners must overcome. Sentiment analysis depends on how text is interpreted and how emotions are categorized as positive, negative, or neutral. The environment in which they are communicated can have an impact on feelings because they are essentially subjective. The dialogue around COVID-19 is extremely complicated and multidimensional, including topics such as politics, the economics, and personal experiences (Schuller et al., 2021). Sentiment analysis algorithms could find it difficult to correctly capture the subtleties and contextual knowledge necessary to analyse sentiments in such a wide range of constantly changing talks. Textual data frequently uses ambiguous terminology, which can make sentiment analysis difficult. People have employed irony and sarcasm to vent their emotions, manage their fears, and even criticise some parts of the crisis response during the epidemic. Automated sentiment analysis algorithms may find it difficult to recognise and understand certain situations effectively, which can cause sentiment categorization errors. The COVID-19 epidemic has afflicted individuals all over the world, producing a significant volume of Multilingual and Multicultural data. Techniques for sentiment analysis may not translate well to different languages or cultural contexts if they were created

for one. The accuracy and dependability of sentiment analysis results can be impacted by translation mistakes, cultural quirks, and variances in sentiment expression between languages. To identify patterns and make predictions, sentiment analysis algorithms significantly rely on training data. However, biases and a lack of representation in the training data utilised in sentiment analysis might provide biased results. For instance, underrepresentation of particular demographics or geographic areas in the training data may result in biased sentiment analysis results. This can have an effect on how varied groups' feelings are understood in the context of COVID-19 and prevent the creation of inclusive and equitable response plans. The COVID-19 epidemic is a continuing catastrophe, and attitudes and opinions may shift over time. Sentiment analysis algorithms that were developed using historical data may have trouble capturing the altering public opinion and changing attitudes that occurred across the various epidemic phases. Real-time sentiment analysis is essential for tracking shifting attitudes and giving decision-makers pertinent information at the right moment. During the COVID-19 outbreak, social media platforms have turned into havens for false information and rumours (Visca et al., 2021). Algorithms for sentiment analysis may unintentionally gather and analyse sentiments linked to inaccurate or misleading information, producing skewed findings. Sentiment analysis in COVID-19 dialogue has a substantial issue in separating sincere feelings from feelings impacted by false information. Sentiment analysis entails examining and evaluating people's verbally expressed sentiments and emotions. It is crucial to take privacy issues and consent concerns into account when gathering and analyzing personal data from social media networks. Conducting sentiment analysis on COVID-19 dialogue requires careful consideration of user privacy protection and data confidentiality. Despite these difficulties and constraints, sentiment analysis continues to be a useful method for gauging public opinion throughout the COVID-19 epidemic (Visca et al., 2021). Through the creation of increasingly complex sentiment analysis tools, enhanced data gathering methodologies, and cross-cultural validation, researchers and practitioners are continuously attempting to overcome these problems (Melton et al., 2021). To get around these issues and improve the precision and application of sentiment analysis in COVID-19 dialogue, collaboration between domain experts, social scientists, and data scientists is crucial. There are a number of difficulties and restrictions with sentiment analysis in COVID-19 dialogue. Subjectivity, ambiguity, issues for multilingualism, and data bias. One of the main difficulties that sentiment analysis practitioners encounter is shifting sentiments, false

information, and ethical issues. The reliability and applicability of sentiment analysis results in interpreting public sentiment, establishing effective communication strategies, and influencing decision-making during the ongoing COVID-19 epidemic depend on recognising and overcoming these problems.

2.7 Deep Learning Models for Sentiment Analysis

Machine learning's area of deep learning has recently attracted a lot of interest and success. It is built using artificial neural networks, which were modelled after the way the human brain is wired up and functions. In a variety of fields, including computer vision, natural language processing, and speech recognition, deep learning models have demonstrated exceptional ability in tackling complicated problems and obtaining cutting-edge performance. Artificial neural networks, which are made up of linked nodes, or artificial neurons, arranged in layers, are at the heart of deep learning (Nicola et al., 2020). These networks have a similar structure to neurons in the human brain, with each node taking in information, processing it, and then creating outputs that are then sent to higher layers. In order for the network to learn progressively abstract representations of the input data, deep learning refers to the existence of numerous hidden layers between the input and output layers. Deep learning's capacity to automatically extract feature representations from unprocessed data is one of its primary benefits. Traditional machine learning techniques frequently call for human feature engineering, in which subject-matter specialists manually create features that extract pertinent information from the data (Yadav and Vishwakarma, 2020). By repeatedly modifying the weights and biases of the neural network during a process known as training, deep learning models may, in contrast, automatically acquire important information. Deep learning models are incredibly versatile and adaptive to different sorts of data because to this characteristic. Large datasets are used to train deep learning models, which frequently calls for a lot of computer power. The network is fed labelled data during training, and model parameters are changed to reduce the discrepancy between anticipated results and actual labels. Typically, stochastic gradient descent is used for this optimisation, which iteratively adjusts the model's parameters based on the gradients of the loss function (Nicola et al., 2020). Sentiment analysis, a branch of natural language processing that focuses on identifying and comprehending the emotions portrayed in textual data, has recently undergone a revolution thanks to deep learning. Among other uses, sentiment analysis is

essential for comprehending public opinion, client feedback, and sentiment on social media. By accurately capturing the rich meaning and context in textual data, deep learning models have shown amazing performance in sentiment analysis tasks.

Numerous sentiment analysis problems, such as sentiment classification, aspect-based sentiment analysis, and sentiment intensity prediction, have been successfully tackled by deep learning models. The goal of sentiment classification is to categorise a text into categories of good, negative, or neutral emotion. On the other hand, aspect-based sentiment analysis focuses on determining the sentiment conveyed towards particular elements or entities referenced in the text (Visca et al., 2021). The goal of sentiment intensity prediction is to determine the strength or level of sentiment in a particular text. Recurrent neural networks and convolutional neural networks are two well-known deep learning architectures that are employed in sentiment analysis. By applying filters across limited portions of the input, CNNs are particularly good at capturing local patterns and correlations in textual data. In challenges requiring sentence-level sentiment categorization, they have demonstrated exceptional performance. However, RNNs have been effectively used in sentiment analysis applications that require capturing the temporal connections between words or sentences since they are well adapted for modelling sequential data. In recent years, more sophisticated designs have been suggested to overcome the problem of vanishing gradients in conventional RNNs, such Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). These designs have enhanced RNNs' capacity to recognise enduring relationships in textual data, which has led to higher performance on sentiment analysis tasks. Additionally, attention methods have been included to enhance sentiment analysis performance of deep learning models. When formulating predictions, attention techniques let the model to concentrate on various input components, efficiently capturing the most instructive and pertinent data for sentiment analysis (Minaee et al., 2021). In sentiment classification tasks, attention-based models have demonstrated promising results, particularly in cases when the sentiment expression is more complicated and needs the capture of minute features.

Arabic text has also been subjected to adaptations and applications of deep learning models for sentiment analysis. Due to the complexity of the Arabic language, which includes its rich morphology, unusual spelling norms, and existence of dialectal variants, Arabic sentiment analysis offers particular difficulties. Researchers have created deep learning models

specifically designed for Arabic sentiment analysis to overcome these issues. These models frequently include Arabic-specific pre-processing techniques including morphological analysis, discretization, and stemming. Arabic word embeddings have also been utilised to improve the representation of Arabic text in deep learning models. These embeddings capture the semantic links between Arabic words. Studies have also looked at the transfer learning method, which involves honing models that have already been trained on substantial Arabic corpora for certain sentiment analysis tasks. With this strategy, the models may utilise their pre-training information and apply it to the sentiment analysis domain (Nicola et al., 2020). Overall, sentiment analysis tasks, particularly those particular to Arabic language, have demonstrated encouraging results for deep learning models. They may improve the efficacy and accuracy of sentiment analysis across a range of fields, allowing for a deeper comprehension of how sentiment is expressed in textual data (Minaee et al., 2021). However, issues including data scarcity, domain adaption, and interpretability continue to be topics of deep learning for sentiment analysis study and development.

By developing robust and efficient methods for identifying sentiment in textual data, deep learning has significantly advanced the area of sentiment analysis. Determine the sentiment or subjective information represented in a text, whether it is favourable, negative, or neutral, using sentiment analysis, sometimes referred to as opinion mining. Deep learning has emerged as a potential method for sentiment analysis in light of the rapid expansion of online information and the growing significance of comprehending public opinion (Minaee et al., 2021). The capacity of deep learning to automatically learn complicated patterns and representations from unprocessed text input is one of the technology's main benefits in sentiment analysis. Traditional methods of sentiment analysis frequently used hand-crafted features or lexicons that needed in-depth topic expertise and physical labour. In contrast, deep learning models may use a vast quantity of labelled data to automatically discover useful features and representations. Deep learning models become more versatile and able to be applied to many domains and languages as a result. In sentiment analysis, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are two popular deep learning architectures (Hussain, Lee and Zeadally, 2018). By using convolutional filters over tiny local areas, CNNs are particularly good at identifying local patterns and relationships within text. They have been particularly useful in jobs that require the determination of the sentiment contained in a single sentence, or "sentence-

level sentiment classification" (Nicola et al., 2020). CNNs can learn to recognise many language elements at different levels, from individual words to phrases and sentence patterns, by utilising hierarchical frameworks. RNNs, on the other hand, excel at modelling sequential data, which makes them a good choice for sentiment analysis jobs that call for capturing the contextual connections between individual words or phrases. RNNs update their hidden state at each stage of the input processing process, allowing them to keep track of previous inputs. They can now recognise long-term dependencies in textual data as a result. The problem of disappearing gradients has been addressed by the development of RNN variants including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), which enable RNNs to better capture long-term relationships. Deep learning models for sentiment analysis now include attention methods that let them concentrate on the most useful sections of the input. According to their significance for sentiment analysis, distinct elements of the input are given varied weights by attention processes. Attention-based models can efficiently capture the most useful characteristics for sentiment categorization by focusing on the most pertinent words or phrases (Minaee et al., 2021). This is especially helpful when the sentiment expression is more intricate and calls for the capture of minute nuances.

Deep learning models have been used to apply transfer learning to sentiment analysis. Transfer learning is the process of pre-training a model on a big dataset, often in a similar task or domain, and then fine-tuning the model on a smaller dataset particular to the current sentiment analysis job. By using this method, the model may apply the information and representations it learnt during the pre-training phase to the sentiment analysis domain. Deep learning models have been proven to perform better in sentiment analysis when transfer learning is used, particularly when there is a dearth of labelled training data. Deep learning models have recently shown cutting-edge performance in a variety of tasks involving sentiment analysis, such as sentiment classification, aspect-based sentiment analysis, and sentiment intensity prediction. They have been effectively used in a variety of fields and languages, demonstrating their adaptability and efficiency in extracting sentiment from textual data. Deep learning models for sentiment analysis do, however, also have significant drawbacks. To function at their best, they frequently need a lot of labelled training data, which might be a constraint in areas with little labelled data. Another difficulty is the interpretability of deep learning models, which are sometimes viewed as "black boxes" and make it challenging to comprehend the underlying causes of their

predictions. Additionally, domain adaptation is still difficult since sentiment analysis models that have been trained on one domain may not work well on another (Yadav and Vishwakarma, 2020). Despite these difficulties, deep learning has unquestionably revolutionised sentiment research by supplying strong methods for extracting sentiment data from text input. Deep learning algorithms and ongoing research are pushing the limits of sentiment analysis to better comprehend how people's thoughts and feelings are reflected in text data.

2.8 Covid-19 Data Analysis

There are numerous researchers on sentiment analysis with diverse social media platforms. In this part we examine the existing work related to COVID-19 data analysis, covering the period from January 2020 to December 2023. This section is focused on four main tasks: social media analysis, chest x-ray image processing, cellular data analysis, and general predictions and forecasts of potential infected cases. The social media analysis includes network graph and text analysis of social networks. The second task involves the use of machine learning and deep learning algorithms to predict cases from chest x-ray images, while the third task analyzes cellular data to forecast infection risks based on handover volume and movement patterns. The final task aims to predict the number of infected cases based on confirmed and death case reports. In the realm of sentiment analysis, there is a scarcity of research works that employ machine learning and deep learning methods to Arabic language datasets. Although numerous studies on sentiment analysis have been published in various languages, the lack of a similar approach using Arabic tweet dataset necessitated its exploration. In this research study, various deep learning approaches and its impact on social media analysis and sentiment analysis has been discussed in the next subsection.

Social networking websites like Facebook and Twitter are commonly employed to obtain datasets for sentiment analysis. The Tweets offer the most current data on users' interests, emotions, habits and views on worldwide occurrences (AlTarrah et al., 2021). During the pandemic of COVID-19, the majority of people paid close attention to social media to stay abreast of the news and express their feelings about it. The deep learning technique has become popular in many fields and has been increasingly used by scientists and data scientists to tackle sentiment analysis, as indicated in the study of Alsudias and Rayson (2020). Moreover, deep learning algorithms are seen to be effective and productive in managing huge datasets.

2.9 Understanding the COVID-19 Pandemic and its Impact

The COVID-19 pandemic, which first surfaced in late 2019, has had a significant effect on society and world health. The initial cases of a unique respiratory sickness were recorded in a seafood market in Wuhan, China, which is where the pandemic's beginnings may be found. A brand-new coronavirus strain known as SARS-CoV-2 was quickly determined to be the cause. The World Health Organisation (WHO) declared the virus a worldwide pandemic in March 2020 as a result of its quick spread and high incidence of morbidity (Laxminarayan et al., 2020). A sickness caused by a member of the coronavirus family can range from the common cold to serious respiratory conditions. Due to its resemblance to earlier outbreaks of Middle East respiratory syndrome (MERS) in 2012 and severe acute respiratory syndrome (SARS) in 2002, the discovery of SARS-CoV-2 as a novel coronavirus strain caused alarm. SARS-CoV-2, however, had unique traits, such as its capacity to spread asymptomatically and the absence of efficient cures (De Simone et al., 2020). The first reaction to the pandemic focused on trying to keep the virus under control in Wuhan, where it had its epicentre. However, the virus swiftly expanded beyond of China's borders, causing regional epidemics and ultimately spreading globally. International airports were as important entrance sites for the virus, which spread quickly because to the worldwide nature of contemporary travel. Governments enacted harsh measures including travel bans, border closures, and lockdowns to stop the spread as cases soared in several nations. When an infected person coughs, sneezes, or speaks, respiratory droplets are mostly how it is spread. These droplets may land on surfaces, which when they are touched may help spread the disease if the person touches their face. Additionally, it has been acknowledged that aerosols, which are tiny respiratory particles, might spread through the air. The COVID-19 pandemic has brought attention to the value of international collaboration and information exchange. In order to research the virus, comprehend its biology, and provide diagnostic tests, scientists and health organisations from all around the world have worked together. The detection of many variations that have developed over time and the tracking of the virus's transmission have both been made possible by genomic sequencing. Additionally, the pandemic has brought attention to the necessity of strong public health systems and preparedness measures. Strong healthcare institutions and efficient monitoring systems have typically helped countries respond to the epidemic more successfully (Mastropietro, Rodilla and

Battle, 2020). However, the crisis has revealed weaknesses in the healthcare systems, such as a lack of medical supplies, overcrowded hospitals, and overworked medical staff. The development of the COVID-19 pandemic has had a profound effect on society and world health. It has become a difficult challenge due to the quick transmission, high morbidity rate, and worldwide interconnection. It is essential to comprehend the pandemic's origins, mechanisms of transmission, and worldwide reaction in order to lessen its effects and guide future preparedness measures. In order to solve the current issue and stop such outbreaks in the future, ongoing research and collaboration are crucial.

In order to understand how infectious illnesses spread and are managed, epidemiology is essential, and the COVID-19 pandemic has been no exception. Epidemiological research has been crucial in identifying the virus's risk factors and modes of transmission. The epidemiology of COVID-19 and its mechanisms of transmission has covered in this section. The clinical symptoms of COVID-19 have shown a wide spectrum, ranging from asymptomatic or moderate instances to severe respiratory disease and even mortality. The typical incubation period, or the interval between exposure and the beginning of symptoms, has been calculated to be between 5 and 6 days, however it can vary from 2 to 14 days (Laxminarayan et al., 2020). Because people might be infectious before they show symptoms or even if they stay asymptomatic for the duration of the virus, the longer incubation period enables silent transmission. When an infected person coughs, sneezes, speaks, or breathes heavily, respiratory droplets are released that are the main way COVID-19 is spread. People who are close to an infected person (within about 6 feet) may inhale these droplets and get infected. The virus can also touch down on objects or surfaces, where it can last for variable amounts of time. A person can spread the virus to their respiratory system if they contact a contaminated surface before touching their face, especially the mouth, nose, or eyes.

The possibility of airborne transmission makes limiting the spread of Covid-19 a difficult task. Although respiratory droplets are the major means of transmission, current research indicates that the virus can also be carried by smaller respiratory particles known as aerosols, which can hang about in the atmosphere for extended periods of time. Concerns are raised by this, especially in confined areas with poor ventilation where aerosols can build up and heighten the risk of transmission. The spread of COVID-19 is made easier by a number of reasons. Even in those with few or no symptoms, the high viral load in the upper respiratory tract is a significant

contributing factor. This implies that even those who do not exhibit symptoms of illness may still release the virus and perhaps spread it to others. Furthermore, crowded interior spaces, close-range talks, and extended exposure are among the activities and environments that encourage close contact and enable the interchange of respiratory droplets that raise the risk of transmission. Public health guidelines and strategies to stop the spread of the virus have been informed by knowledge of the epidemiology and routes of transmission of Covid-19 (Bi et al., 2020). These include using face masks in public places, keeping a physical distance, often washing your hands, and enhancing ventilation inside. In order to isolate sick people and stop the spread of the disease, testing, contact tracking, and quarantine procedures have also been extremely important. The epidemiology of COVID-19 has shed important light on the trends in viral transmission and its risk factors. Although respiratory droplets continue to be the predominant mechanism of transmission, aerosols also have the ability to spread diseases through the air. Public health initiatives designed to stop the spread of the virus have been influenced by knowledge of these ways of transmission. In order to contain and lessen the effects of the pandemic, ongoing research and monitoring is continue to help us understand the epidemiology of COVID-19.

From asymptomatic or moderate instances to severe respiratory sickness and consequences, COVID-19's clinical symptoms can range greatly. For effective management and public health responses, it is essential to comprehend the range of clinical manifestations. The clinical signs and symptoms of COVID-19 and their effects on public health would be covered in this section. The most typical COVID-19 symptoms include fever, coughing, and shortness of breath. Fatigue, pains in the muscles and body, a sore throat, a loss of taste or smell, a headache, and gastrointestinal symptoms including nausea, vomiting, or diarrhoea are some other symptoms that may be present. It is significant to highlight that each person's symptom intensity might vary; some people experience very minor symptoms, while others experience severe disease that necessitates hospitalisation. Acute respiratory distress syndrome (ARDS), a serious lung damage that may need for mechanical ventilation, can result from severe COVID-19 instances (Visca et al., 2021). The virus can also harm other organs, including the heart and kidneys, as well as the nervous system. People who are older and those who have underlying medical issues including diabetes, hypertension, obesity, or immunocompromised status are more likely to experience severe sickness and unfavourable results. There has been a significant influence of

COVID-19 on public health. Healthcare systems throughout the world are under strain as a result of the virus's fast spread and capacity to cause serious sickness. In addition to managing the inflow of patients, hospitals and healthcare institutions have had difficulty finding enough hospital beds, ventilators, and personal protective equipment (PPE) as well as safeguarding healthcare employees from infection.

In addition to having an immediate effect on a person's health, COVID-19 has had significant negative effects on both public health and society at large. Lockdowns, travel restrictions, and social withdrawal have all been put in place to impede the virus's spread, but they have also had a substantial economic impact. These policies have disrupted economies, causing numerous people and communities to experience financial hardships, job losses, and company closures. Additionally, the epidemic has brought existing health inequities to light and made them worse (Hussain, Lee and Zeadally, 2018). A few groups have been disproportionately impacted by COVID-19, including low-income communities, racial and ethnic minorities, and marginalised groups. These groups are more vulnerable because of things like poor access to healthcare, congested living situations, and greater incidence of underlying health issues. Several important efforts have been the focus of the public health response to COVID-19. Identification and isolation of infected people to stop further infection has required testing and contact tracing. By giving people protection and lowering the intensity of disease, vaccination initiatives have also been crucial in decreasing the effect of the virus. Promoting preventative measures including mask use, hand cleanliness, and physical separation has relied heavily on public health messaging and education (Savarese and Lund, 2017). COVID-19's clinical symptoms can range from moderate sickness to severe illness, with some people developing serious respiratory and multiorgan problems. In addition to taxing healthcare systems, upsetting economies, and escalating health inequities, the impact on public health has been significant. A comprehensive strategy, including testing, contact tracing, immunisation, and public health message, was needed to respond to the epidemic. To safeguard the general public's health and lessen the pandemic's long-term effects, ongoing monitoring and mitigation activities are required.

Globally, society and economies have been disrupted by the COVID-19 epidemic, which has had severe social and economic repercussions. The social and economic effects of the epidemic has covered in this part, along with the difficulties that people, groups, and corporations have to deal with. The introduction of different containment measures including lockdowns, travel

restrictions, and social distance rules has been one of the pandemic's direct societal repercussions. These actions have had a tremendous impact on daily life, leading to the shutdown of public buildings like schools and companies. The forced isolation and decreased social connections have had a significant negative influence on people's mental health, with more people reporting symptoms of anxiety, despair, and loneliness. The epidemic has had a significant impact on education as well. Millions of children's educations throughout the world have been interrupted by school closings and the move to remote learning. For students from impoverished families who might not have access to dependable internet connections or appropriate technology, the shift to online learning has brought obstacles. Many pupils' learning results and future possibilities are anticipated to be negatively impacted in the long run by the educational gaps brought on by the epidemic (Hussain, Lee and Zeadally, 2018). The pandemic's economic effects have been widespread. Small and medium-sized businesses (SMEs) in particular have experienced business closures, bankruptcies, and layoffs. Since travel restrictions and lower consumer spending have resulted in a drop in demand, several businesses, including hospitality, tourism, and retail, have been negatively impacted. Financial difficulty for individuals and families as a result of the loss of employment and income has raised poverty rates and food insecurity in many places.

In addition, the epidemic has highlighted and widened already-existing social and economic disparities. The economic crisis has disproportionately impacted some groups, including low-income people, gig workers, and marginalised communities. These populations are especially susceptible to the negative effects of the pandemic because they frequently lack access to financial resources, healthcare, and social support networks. The pandemic's social and economic effects have also had gender-specific repercussions (Savarese and Lund, 2017). Women have been disproportionately impacted, suffering from higher rates of job loss, more burdensome caregiving duties, and increased susceptibility to domestic abuse. Due to the fact that they are frequently the ones in charge of childcare and home schooling, women have been put under additional stress as a result of the closure of schools and childcare facilities. Different governments have taken different actions to lessen the pandemic's social and economic effects. To help people and companies, economic stimulus plans, financial assistance programmes, and social welfare initiatives have been put in place. The provision of interim relief for people impacted by job losses and financial hardship has been made possible in large part through

unemployment benefits, cash transfers, and rent moratoria. The epidemic has also brought attention to the necessity of improving healthcare and social safety nets. It has emphasised the necessity of universal access to inexpensive healthcare as well as the significance of strong social safety nets to assist people and communities in difficult times (Thakkar and Patel, 2015). The COVID-19 pandemic has had a significant impact on social and economic life across the world. Education has been interrupted and mental health has suffered as a result of confinement measures and the consequent social isolation (Nicola et al., 2020). The economic repercussions have expanded inequality, caused job losses, and closed down businesses, particularly hurting disadvantaged communities. Government assistance initiatives and interventions have been essential in easing some of the difficulties that people and companies have to deal with. In the future, it is crucial to address the social and economic inequalities that the epidemic has brought to light and to create resilient institutions that can better resist future crises.

In addition to affecting physical health, the COVID-19 pandemic has also had a negative impact on mental health and general wellbeing. Lockdowns, social exclusion, and isolation were among the techniques taken to stop the virus's spread, but they also made people more stressed, anxious, and distressed psychologically. The anxiety and uncertainty surrounding the virus has been one of the main reasons affecting mental health during the epidemic. There is widespread dread and worry due to COVID-19's quick spread, the large number of cases and fatalities, and the absence of a known treatment or vaccination. Stress and concern levels have also increased as a result of continual exposure to news and information about the epidemic through numerous media outlets. Lockdowns and other social distancing tactics have had substantial psychological effects due to the social isolation and restricted social connections they have caused. Humans are social creatures, and the abrupt disruption of regular social relationships and routines has resulted in emotions of isolation, loneliness, and despair (Stephan, 2018). These sentiments have been made worse by the inability to connect with family, friends, and other support systems; this has been especially difficult for those who live alone or for those who already have mental health problems. Additionally, the epidemic has hampered access to support networks and services for mental health. There are now fewer options accessible for those in need as a result of several mental health establishments being forced to scale back or discontinue in-person services. Everyone has not been able to make the shift to online treatment or telepsychiatry since not everyone has access to reliable internet connections or private venues for conducting virtual

therapy sessions. Many people now face hurdles to receiving mental health treatment, which leads to unmet needs and heightened suffering. The pandemic's economic effects, including job losses and financial distress, have had a negative influence on mental health. Feelings of uneasiness, worry, and despair may result from the lack of income and financial security. Financial pressures, such as unstable housing and the inability to satisfy basic requirements, can have a serious negative influence on mental health.

The pandemic's effects on mental health have disproportionately impacted some communities. Frontline healthcare personnel have suffered from significant levels of stress, burnout, and post-traumatic stress symptoms due to their increased workloads, exposure to the virus, and the emotional toll of caring for seriously ill patients. Children and teenagers have also been impacted, experiencing interruptions in their routines, social relationships, and educational opportunities. The elderly have experienced increased concern and dread for their health and well-being since they are more likely to get serious illnesses from COVID-19 (Scoglio et al., 2019). During the epidemic, efforts have been made to treat mental health. To guarantee ongoing access to mental health care, mental health organisations and specialists have set up online resources, helplines, and virtual support groups. Governments and healthcare systems have acknowledged the significance of mental health and have put into place policies to advance wellbeing, such as awareness-raising campaigns for mental health and the incorporation of mental health services into primary healthcare settings (Thakkar and Patel, 2015). Prioritising mental health and wellbeing both during and after the epidemic is essential going ahead. This entails making sure that mental health treatments are available and inexpensive, supporting healthcare professionals, putting preventative measures in place to deal with upcoming crises in mental health, and lowering the stigma associated with mental illness. To recover from the pandemic's psychological effects and create a society that is healthier and more resilient, communities must invest in resilience-building programmes and mental health support networks.

2.10 Benefits and Challenges of using Deep learning Approaches in Sentiment Analysis

Deep learning approaches have gained significant traction in sentiment analysis due to their ability to automatically learn and extract meaningful features from raw text data. One major benefit is the feature learning capability of deep learning models. These models can autonomously identify and capture complex patterns and dependencies in text, eliminating the need for manual feature engineering. Scholarly research, such as a study by Al-Twairesh et al. (2021) has shown that deep learning models outperform traditional machine learning algorithms in sentiment analysis tasks. Another advantage lies in the representation learning ability of deep learning models. By learning hierarchical representations of text, these models can capture different levels of semantics and contextual information, enabling them to better comprehend the meaning and sentiment expressed in text. For instance, Antoun, Baly, and Hajj (2020) demonstrated the effectiveness of deep convolutional neural networks (CNNs) in sentiment analysis, achieving state-of-the-art performance on multiple benchmark datasets.

Deep learning models are also advantageous in handling large-scale datasets, which is particularly relevant in sentiment analysis tasks that involve a vast amount of text data. For example, Butt et al. (2021) utilized deep neural networks to process millions of Twitter messages for sentiment analysis, showcasing the efficiency of deep learning in handling extensive data.

On the other hand, there are several challenges associated with using deep learning approaches in sentiment analysis. Acquiring labeled training data is a significant challenge, as sentiment annotation is subjective and time-consuming. Liang et al. (2022) highlighted the scarcity of large-scale labeled sentiment analysis datasets as a hurdle in deep learning-based sentiment analysis research.

Interpretability and ability pose another challenge. Deep learning models often act as black boxes due to their complex architectures and numerous parameters, making it difficult to understand how predictions are made or attribute sentiment to specific textual cues. Researchers are actively working on developing methods to enhance the interpretability of deep learning models in sentiment analysis (AlTarrah et al., 2021).

Additionally, generalization of data can be problematic. Deep learning models are susceptible to datasets when trained on limited or unbalanced sentiment analysis datasets, hindering their

ability to generalize to unseen data. Mostafa et al. (2021) emphasized the need to address deep learning-based sentiment analysis for improved robustness and generalization.

Precisely, deep learning approaches offer benefits such as automatic feature learning, representation learning, and efficient handling of large-scale data in sentiment analysis. However, challenges related to data availability, interpretability, and generalization need to be addressed through ongoing research to enhance the performance and usability of deep learning models in sentiment analysis tasks.

2.11 Detecting Real News in Social Media

In addition to creating a crisis in world health, the COVID-19 pandemic has also resulted in an increase in the dissemination of false information and fake news. Social media sites like Twitter, Facebook, and WhatsApp have developed into thriving hubs for the spread of erroneous information about the epidemic. Misinformation can include everything from incorrect claims about the virus's origin to exaggerated statistics, conspiracies, and untested therapies. Many causes contributed to the propagation of false information during the COVID-19 epidemic. First off, social media's quick information distribution capabilities make it challenging to confirm the veracity of the shared content. Furthermore, the pandemic's high levels of uncertainty and anxiety provide an ideal environment for the propagation of rumours and conspiracy theories. Without checking its veracity, people could be more likely to accept and spread information that supports their preconceived notions or worries (Hussain, Lee and Zeadally, 2018). Misinformation is also amplified by social media algorithms. These algorithms are made to promote material that receives plenty of comments, shares, and likes. As a result, sensational or deceptive information could be more visible and reach more people. Social media's viral nature further hastens the dissemination of false information since users frequently share content without checking its veracity (Savarese and Lund, 2017). The effects of spreading false information during a public health emergency like COVID-19 are extensive. False information can damage people's confidence in public health authorities and professionals, which can result in disregard for advised recommendations and treatment regimens. Increased transmission rates and unnecessary fatalities are only a couple of the negative consequences this can have on public health outcomes. The spread of stigma, prejudice, and fear among groups is further facilitated

by misinformation, which worsens the pandemic's effects on society. Various tactics have been used to combat the spread of false information. The public may only receive correct information if erroneous claims are refuted and provided by fact-checking organisations. In order to disprove false narratives, these organisations assess the reliability and quality of material being shared on social media and produce fact-checks. To mark or restrict the exposure of disputed information, partnerships between social media companies and fact-checking organisations have been developed (Savarese and Lund, 2017). Another strategy for battling disinformation is through educational programmes and public awareness campaigns. People can be equipped to assess the authenticity and dependability of information they come across online by fostering media literacy and critical thinking abilities. Campaigns have been started by governments and public health organisations to disseminate correct and current information on COVID-19, highlighting the significance of relying on reliable sources and double-checking information before sharing. In addition, social media sites themselves have taken steps to slow the dissemination of false information. The algorithms have been changed to promote information from reliable sources and to downgrade or delete information that has been marked as inaccurate or deceptive. Users may now report suspected false information via improved user reporting tools, which enables platforms to take the necessary action. Despite these initiatives, it is still difficult to stop the dissemination of false information. It is challenging to recognise and refute every false claim in real-time due to the enormous volume of information broadcast on social media. False narratives are more difficult to disprove because of how quickly disinformation travels and how slowly fact-checking attempts are completed. Furthermore, the worldwide reach of social media platforms makes it difficult to battle false information in a range of linguistic and cultural situations. Public health and overall well-being have been severely hampered by the transmission of false information during the COVID-19 epidemic. Social media's quick spread and viral nature have made it easier for incorrect information to spread, weakening attempts to contain the epidemic and harming both people and communities. However, progress may be achieved in battling false information and spreading factual information during public health crises by working together with fact-checkers, social media platforms, and public awareness campaigns.

The accuracy and dependability of information must be maintained at all times, but especially at times of crisis like the COVID-19 epidemic. Misinformation that is being spread on social

media platforms has been identified and addressed using a variety of tools and techniques. These tactics include both automatic and human fact-checking methods that make use of artificial intelligence and machine learning algorithms. Manual fact-checking requires human involvement in determining the truthfulness of assertions and dispelling false information. Fact-checkers use thorough investigation methods to confirm facts. They are frequently recruited by respectable news organisations or specialised fact-checking companies (Hussain, Lee and Zeadally, 2018). To determine the truthfulness of assertions, they depend on reliable sources, professional judgements, government documents, and original data. Fact-checkers look for contradictions, logical errors, and a lack of supporting data in statements. They release fact-checking reports that offer a thorough examination of the assertion and the data proving or disproving it. In order to successfully battle false information, fact-checking organisations frequently work with social media platforms. To analyse and flag controversial information, platforms like Facebook and Twitter have partnered with reliable fact-checking groups. These partnerships make it possible to detect misleading information and lessen its exposure. Fact-checkers may label or include a warning when a claim is found to be untrue in order to give consumers accurate information (Nicola et al., 2020). A lot of social media sites provide users the ability to report content that they think contains false information. User reports are essential for highlighting content that may be inaccurate or deceptive so that platform administrators or fact-checkers may evaluate it. Platforms have put in place user reporting methods to streamline the process and increase user involvement in spotting and battling false content.

Automated methods utilising machine learning (ML) and artificial intelligence (AI) algorithms are being developed to aid in the identification of false information. To determine the veracity of material, these algorithms examine patterns, language signals, and contextual data. Techniques for Natural Language Processing (NLP) are frequently used to comprehend and categorise text data. To identify similar patterns in new material, machine learning algorithms, such as supervised and unsupervised learning, are trained on vast datasets of known misinformation. These two methods can provide light on the spread of false information. The source of incorrect information may be located and networks of users disseminating it can be found by examining the information flow. Understanding the dynamics of information dispersion and the role that certain individuals play in the transmission of false information is made possible through social network analysis. The creation of counter-messaging campaigns

and tailored treatments can both benefit from this understanding. Platforms for crowdsourcing and efforts for citizen journalism make it possible for people to work together to find and confirm information. These platforms enable people to contribute their knowledge, analysis, and supporting or refuting data. The fact-checking process may be sped up using crowdsourcing, which also makes use of the varied group's aggregate intelligence. Promoting media literacy and critical thinking abilities among the general people is essential in the fight against disinformation. Users can be empowered to become informed consumers of information via educational programmes that show people how to assess information sources, fact-check assertions, and recognise common strategies used to propagate misinformation. The effects of false information can be reduced by giving people the tools to critically analyse information. Although there has been improvement in identifying false information, problems still exist. Misinformation changes swiftly, with new strategies and stories frequently appearing. It is vital to constantly update and enhance detection approaches because adversarial actors purposefully alter their tactics to elude detection algorithms. The worldwide reach of social media platforms makes it difficult to combat disinformation in a range of linguistic and cultural contexts (Yadav and Vishwakarma, 2020). The use of manual fact-checking, partnerships with social media platforms, user reporting mechanisms, algorithmic solutions, data mining and network analysis, crowdsourcing, and media literacy programmes are all examples of tactics and approaches for spotting false information. To successfully combat disinformation and ensure the distribution of correct and reliable information, a multifaceted strategy that combines human experience with technical breakthroughs is required.

2.12 Research Gap

Based on the previous studies on different deep learning approaches used for sentiment analysis, there are several potential research gaps that can be addressed in future work. However, if conducting a new study, one potential research gap that could be addressed is the limited focus on interpretability of RNN, CNN and LSTM based models for sentiment analysis. This could involve exploring ways to visualize the attention weights generated by the model to identify the words or phrases that are most important for the sentiment prediction. Additionally, it could involve exploring ways to incorporate external knowledge sources, such as sentiment lexicons or domain-specific knowledge, to improve the interpretability of the model. Although, there

have been several studies on sentiment analysis of Covid-19-related tweets, there is a research gap in analyzing the sentiment of Gulf opinion leaders towards Covid-19. The minimal attention paid to certain geographic locations is one possible gap in the literature that might be filled up by upcoming studies. There is a need for further research that look at sentiment analysis and social media use in different locations, even though the thesis only looks at these topics in the Arab world. Researchers can give a more thorough picture of public attitudes and information sharing during the COVID-19 epidemic by examining sentiment analysis and social media use in locations like Europe, Asia, or Africa. The study make it possible to compare sentiment and social media trends across various cultural contexts, enabling researchers to spot any regional variances in the way the public feels and how information is disseminated. Examining sentiment analysis outside of Twitter would fill another vacuum in the literature that may be investigated in future studies. While the thesis focuses on sentiment analysis in Arabic language on Twitter, there are other social media sites like Facebook, Instagram, and YouTube that are important for information exchange during the epidemic. To develop a more comprehensive picture of public sentiment and information distribution, future research might look at sentiment analysis and social media use on these platforms. This research provides light on whether sentiment patterns change across various social media platforms as well as how different platforms affect public opinion and the dissemination of information. Additionally, further study is required to determine how sentiment analysis and social media usage affected public health practises throughout the epidemic. Although the thesis examines sentiment analysis and public perceptions, there may be a void in the research when it comes to the impact of social media and sentiment analysis on people's health-related behaviours. Future studies should look into how social media sentiment affects people's willingness to follow public health recommendations including wearing masks, keeping social distance, and getting vaccinated.

2.13 Chapter Summary

In summary, chapter 2 provides an overview of the literature review conducted for the proposed study on sentiment analysis in the context of social media, specifically on Twitter. The chapter situates the research topic within the broader context of sentiment analysis, including its definition, methods, and applications. It explores the current state of research on sentiment

analysis related to COVID-19, including studies that have used machine learning and deep learning approaches, such as CNN and RNN algorithms. This chapter also investigates deep learning approaches for Arabic sentiment analysis, including techniques for Arabic language processing. The chapter identifies research gaps and informs the research methodology and approach for the proposed study.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction to the Chapter

This chapter describes the methodology used to conduct the research on Arabic sentiment analysis for Gulf opinion leaders using a deep learning approach case study based on Covid-19. The study utilizes a deep learning approach to perform sentiment analysis on Arabic datasets collected from Twitter and other social media. The methodology comprises several steps, including data collection, pre-processing and word embedding by applying a deep learning algorithm. Also, evaluating the effectiveness of the experiment using metrics such as accuracy, F-score, recall, and precision. This chapter discusses each step in detail and explains the rationale behind the selection of the datasets, selection criteria for opinion leaders, and the three deep learning architectures (RNN, LSTM and CNN) used in the experiment. The methodology is designed to provide a comprehensive and systematic approach to analyzing the sentiment expressed by Gulf opinion leaders on Twitter regarding Covid-19.

3.2 Investigation Method

This investigation of this research utilized an approach to perform sentiment analysis on Arabic datasets that includes the steps outlined in the flow chart given by Albahli (2022). Initially, the data was collected from Twitter. Then the data was pre-processed and cleaned. Word embedding was applied so that the words could be converted into vectors and then a deep learning algorithm was used on the processed data to classify it into three binary numbers 1, 0 and -1 by using SMOTE (statistical technique to analyze dataset in a balanced manner). The three model architectures were used as a deep learning approaches that are RNN, CNN and LSTM. Therefore, to evaluate the experiment's effectiveness, metrics such as accuracy, F-score, recall and precision were employed.

3.3 Data Extraction

For this research, data was collected from Twitter related to Gulf opinion leaders and Covid-19. The data was collected using Twitter's Application Programming Interface (API) and was limited to tweets posted in Arabic. The API allowed the collection of tweets that matched specific keywords, hashtags, or user accounts. A combination of these search parameters was used to collect relevant tweets. The search terms included keywords related to Covid-19, such as "coronavirus," "pandemic," "vaccine," and so on, and hashtags that were commonly used in the Gulf region, such as #UAE, #KSA, #Qatar, #Oman, and #Bahrain.

The data collected for testing phase has been taken from January 1, 2022, to June 30, 2022. During this period, the Twitter API is used to collect a total of 100,000 tweets as a test data related to Gulf opinion leaders and Covid-19. A set of selection criteria was used for opinion leaders to ensure the quality and relevance of the data. The focus was on users who had a significant number of followers and were active in posting about Covid-19 in the Gulf region. Users who were known for their expertise or influence in the field, such as healthcare professionals, government officials, and media personalities, were also considered.

The data collection process was conducted in two stages. First, the search parameters were used to collect a large volume of tweets. Then, the selection criteria were applied to identify tweets posted by opinion leaders. In the second stage, the Twitter API was used to retrieve the historical tweets of the identified opinion leaders for the last six months, from January 1, 2022, to June 30, 2022. The collected tweets were stored in a database and underwent pre-processing and cleaning to remove irrelevant information, such as retweets, duplicates, and non-Arabic tweets. The pre-processed data was used for further analysis using deep learning approaches for sentiment analysis. The stage 1 process has shown in the below figure.

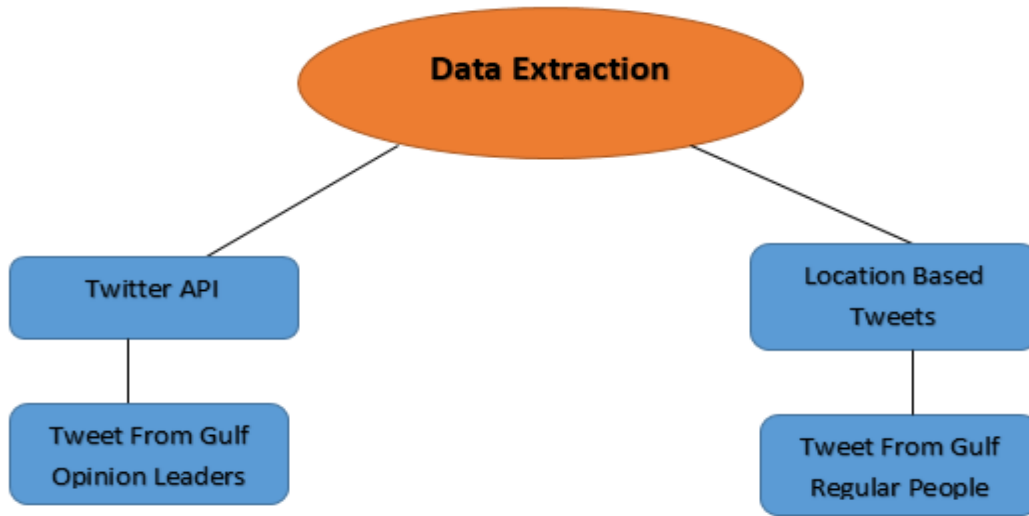


Figure 1: Step 1 process of data extraction

3.3.1 Dataset Description

The dataset contains a mix of tweet types, including original tweets and retweets, and covers a range of topics related to Covid-19 in the Gulf region. The dataset was labeled using a three-point scale, where 1 denotes positive sentiment, -1 denotes negative sentiment, and 0 denotes neutral sentiment. The labelling was performed manually by a team of Arabic language experts to ensure the accuracy and consistency of the labels. The labeled dataset was divided into training, validation and testing sets with a split ratio of 80:10:10, respectively. The training set was used to train the deep learning models, while the validation set was used to fine-tune the model hyper parameters and avoid over fitting. For the Arabic Sentiment Analysis task, this research consider using the following datasets:

- Arabic Twitter Sentiment Corpus (ATSC)
- Arabic Sentiment Analysis Dataset (ASAD)
- SemEval-2017 Task 4A: Sentiment Analysis in Twitter

3.3.2 Selection Criteria for Opinion Leaders:

The selection criteria for opinion leaders depend on the specific research questions and objectives of the study. However, the following factors for selecting opinion leaders can be considered:

- Number of followers on social media
- Frequency and relevance of their posts related to the topic
- Expertise and reputation in the field
- Geographic location within the Gulf region

3.3.3 Rationale behind choosing the three deep learning architectures:

The three architectures are popular deep learning models used for natural language processing tasks such as sentiment analysis. Each architecture has its strengths and weaknesses, and their performance may vary depending on the specific characteristics of the dataset and the task at hand. Here is a brief rationale for choosing these architectures:

- RNN (Recurrent Neural Network) is suitable for handling sequential data such as text and can capture long-term dependencies between words.
- CNN (Convolutional Neural Network) is effective in identifying local patterns and features in the text, and it can be faster to train compared to RNN.
- LSTM (Long Short-Term Memory) is an extension of RNN that can address the vanishing gradient problem and preserve important information over long sequences.

3.4 Data Pre-processing and Cleaning

The collected dataset underwent pre-processing and cleaning to remove irrelevant information and prepare it for deep learning-based sentiment analysis. The pre-processing steps included removing URLs, hashtags, user mentions, and special characters, as well as tokenization, stemming, and stop-word removal (Emaduddin et al., 2022). Initially, all URLs were removed using regular expressions, as they do not contribute to the sentiment of the tweets. Then, all hashtags and user mentions were also removed, as they are not informative for sentiment

analysis. Special characters, such as punctuation marks and emoticons, were also removed to improve the efficiency of the deep learning algorithms.

The pre-processing steps has continued with tokenization, where the tweets were segmented into individual words or tokens. The tokens were then stemmed to their root form, which helps to reduce the size of the dataset and avoid redundancy. Finally, stop-words, such as articles, conjunctions, and prepositions, were removed to eliminate noise and improve the accuracy of the sentiment analysis.

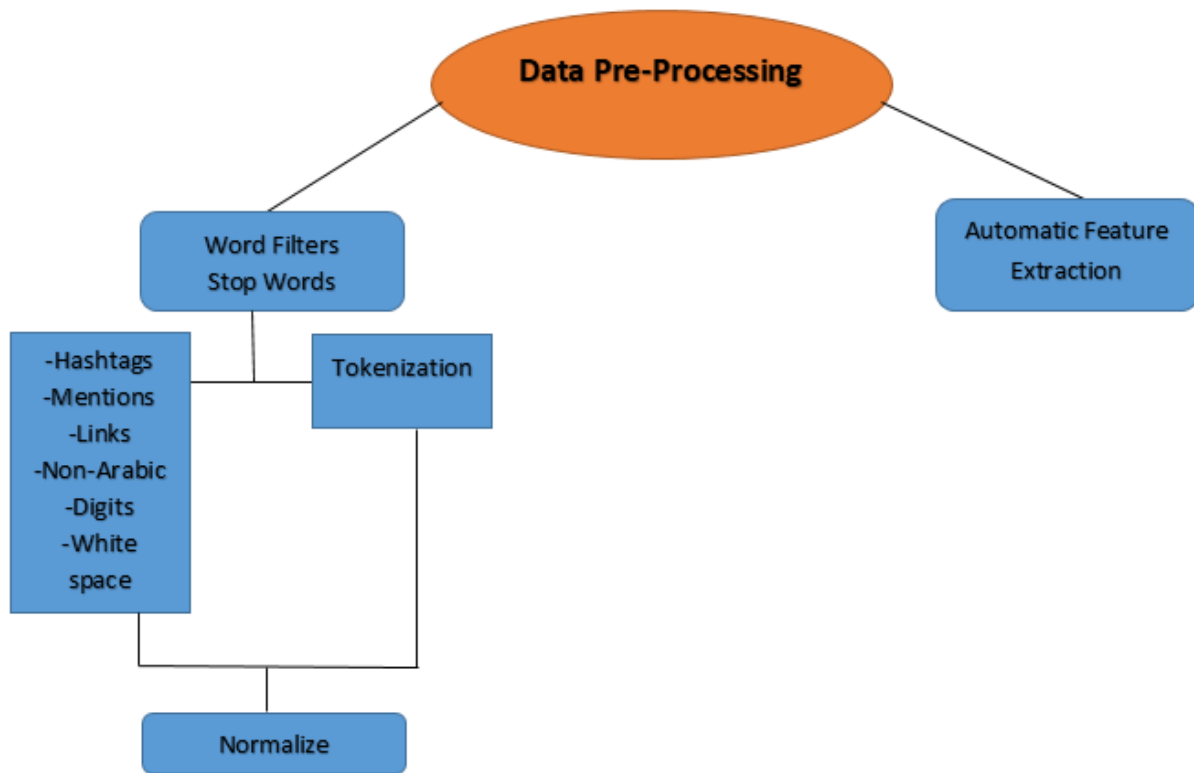


Figure 2: Step 2 Process of Data Pre-Processing

After the pre-processing steps were completed, the data was checked for duplicates and non-Arabic tweets. Any duplicates were removed to avoid bias in the dataset, while non-Arabic tweets were filtered out to ensure that only Arabic tweets were used in the analysis. Finally, the dataset was reduced to approximately 65,000 Arabic tweets. This reduction was mainly due to the removal of duplicates and non-Arabic tweets, as well as the removal of stop-words and other noise. The remaining tweets were of high quality and relevance to the research, and were suitable for further analysis using deep learning-based sentiment analysis techniques.

The pre-processed data was then converted into numerical vectors using word embedding techniques, where each word was represented by a vector of real numbers. This step enabled the use of deep learning algorithms, which require numerical inputs as mentioned above (1, -1, and 0). The pre-processed and embedded data was then labeled using a three-point scale, as described in the previous section, and divided into training, validation, and testing sets for further analysis.

3.4.1 Word Embedding

Word embedding is a technique used to convert words into numerical vectors, which can be used as inputs to deep learning algorithms. In this research, the pre-processed tweets were converted into word embedding using the Word2Vec algorithm. The Word2Vec algorithm uses a neural network to learn the relationships between words in a corpus, and represents each word as a vector of real numbers (Ombabi et al., 2017). The vectors capture the semantic and syntactic relationships between the words, enabling the deep learning algorithms to understand the meaning and context of the text.

The Word2Vec algorithm was trained on the pre-processed dataset using a skip-gram model, which predicts the context words given a target word. The dimensionality of the vectors was set to 300, which has been shown to provide a good balance between accuracy and efficiency. Once the Word2Vec model was trained, the pre-processed tweets were converted into vectors by averaging the vectors of the individual words in each tweet. This approach is known as the "bag of words" model, which assumes that the order of the words in the text does not matter for sentiment analysis (Kasri, Birjali and Beni-Hssane, 2019). The resulting vectors were then used as inputs to the deep learning models, enabling them to learn the relationships between the words and classify the tweets into positive, negative, or neutral sentiment.

3.5 Classification of Data

The classification process involved assigning each tweet a label of either 1, 0, or -1, corresponding to positive, neutral, or negative sentiment, respectively. The labels were assigned

based on the sentiment of the tweet as determined by the pre-processing and word embedding steps. Once the labels were assigned, the dataset was oversampled using SMOTE to balance the distribution of the classes. The oversampling process involved creating synthetic examples of the minority classes using the SMOTE algorithm. The resulting dataset was then used as input to the deep learning models. See the example in the figure below.

Tweets	Sentiment
الله يعز المملكة ❤️ الحمد لله اخذنا اول جرعة من لقاح كورونا	1
الاكتئاب قاعد ينتشر اكثر من كورونا.	-1
س: هل أخذ الزنك يقيني من فيروس كورونا ج: لا س هل اذا أخذت الكلوركوين او هيدروكسيكلوركوين يحميني من الكورونا ج لا البرتوكول ليس للاستخدام الشخصي بل للمختصين في المستشفيات ولا تحاول اقتناء اي من الأدوية والأدوية لا تغني عن العناية الصحية والعزل وهي الأساس في اغلب الحالات	0

Figure 3: Example of tweets showing the assigned labels with binary numbers

By classifying the pre-processed and embedded tweets into three binary numbers using SMOTE, the deep learning algorithms were able to learn the relationships between the words and the sentiment of the tweets, and classify them into positive, negative, or neutral sentiment. This classification enabled the identification of the sentiment of Gulf opinion leaders towards the COVID-19 pandemic, providing valuable insights into the public perception of the pandemic in the Gulf region.

3.6 Applying a deep learning algorithm on the processed data

At this stage of research, the pre-processed tweets are ready to be classified using deep learning algorithms. In this research, three different deep learning architectures were applied: Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs).

RNNs are a type of neural network that can handle sequential data, such as text, by processing each word in the sequence one at a time (Zulqarnain et al., 2019). CNNs, on the other hand, are primarily used for image recognition, but can also be applied to text data by using 1D convolutional filters to extract features from the text (Khan et al., 2020). LSTMs are a type of

RNN that can remember information over long periods of time, enabling them to handle complex relationships between words.

The deep learning models were implemented using the Keras framework, which provides an easy-to-use interface for building and training deep learning models. The models were trained on the pre-processed and embedded dataset, with the labels assigned during the pre-processing stage. A statistical technique called Synthetic Minority Over-sampling Technique (SMOTE) was used to handle class imbalance in the dataset (Tarawneh et al., 2020). SMOTE generates synthetic examples of the minority class to balance the dataset, improving the accuracy of the models (Mukherjee and Khushi, 2021). The deep learning models were trained using a batch size of 64 and a maximum number of epochs of 30, with early stopping used to prevent over data. The models were evaluated using several performance metrics, including accuracy, precision, recall, and F1-score, and the best performing model was selected for further analysis.

3.7 Using Architectures as a Deep Learning Approaches

The three deep learning models were chosen for checking their performance ability to handle sequential data and their success in natural language processing tasks. All three model architectures were trained and tested on the pre-processed and embedded dataset using a binary cross-entropy loss function and Adam optimizer. The models were evaluated based on their performance metrics such as accuracy, F-score, recall, and precision to determine their effectiveness in classifying the tweets into the three sentiment categories.

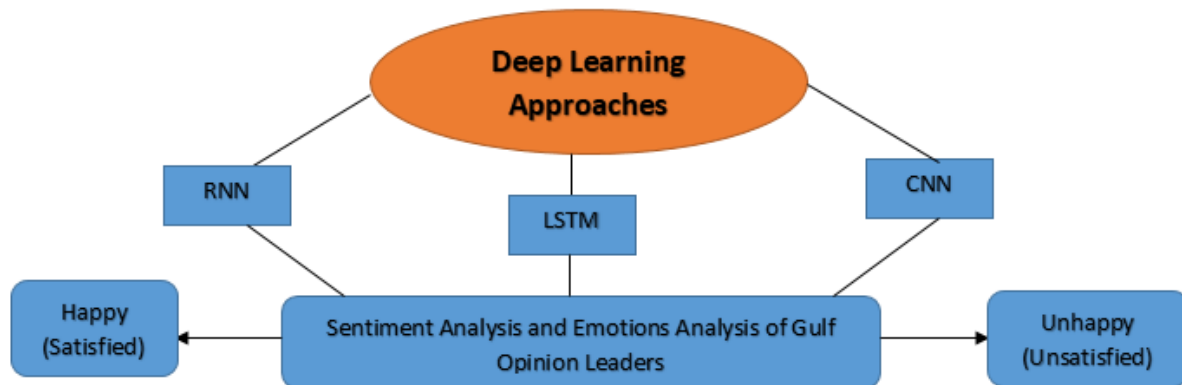


Figure 4: Process of using deep learning approaches

3.7.1 Recurrent Neural Network (RNN)

The first model architecture used was Recurrent Neural Network (RNN), which is well suited for processing sequential data. Salim et al. (2020) studied that RNN model was designed to analyze the sequences of words in the pre-processed tweets and learn the patterns and relationships between them to classify the tweets into the three sentiment categories.

3.7.2 Convolutional Neural Network (CNN)

The second model architecture used was Convolutional Neural Network (CNN), which is known for its ability to extract features from inputs with a grid-like topology, such as images and text (Khan et al., 2020). The CNN model was used to identify important features from the pre-processed tweets and learn the patterns and relationships between them to classify the tweets into the three sentiment categories.

3.7.3 Long Short-Term Memory (LSTM)

The third model architecture used was Long Short-Term Memory (LSTM), which is a type of RNN that is specifically designed to handle the problem of vanishing gradients in the traditional

RNN model (Muhammad, Kusumaningrum and Wibowo, 2021). The LSTM model was used to analyze the long-term dependencies between the words in the pre-processed tweets and learn the patterns and relationships between them to classify the tweets into the three sentiment categories.

3.8 Evaluation of Metrics

In this research, several evaluation metrics were used to evaluate the effectiveness of the deep learning models for sentiment analysis on Arabic text data. These metrics include accuracy, F-score, recall, and precision.

3.8.1 Accuracy

Accuracy measures the proportion of correctly classified tweets to the total number of tweets in the dataset (Sadiq et al., 2021). It evaluates how often the model correctly classified the tweets into the three sentiment categories. The formula for accuracy is given by:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Where, TP (True Positive) is the number of positive tweets that were correctly classified, TN (True Negative) is the number of negative tweets that were correctly classified, FP (False Positive) is the number of neutral or negative tweets that were incorrectly classified as positive, and FN (False Negative) is the number of positive tweets that were incorrectly classified as neutral or negative.

3.8.2 F-score

F-score is a weighted average of precision and recall that takes into account both false positives and false negatives (Adhao and Pachghare, 2020). It is a good metric to use when the dataset is imbalanced.

$$\text{Formula: F-score} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

Where, precision is the proportion of true positives among all positive predictions made by the model, and recall is the proportion of positive instances that are correctly identified by the model.

3.8.3 Recall

The recall metric quantifies the model's ability to correctly identify positive instances. In the context of sentiment analysis, recall measures the proportion of positive tweets that were accurately classified by the model (Jain, Saravanan and Pamula, 2021).

$$\text{Formula: Recall} = \text{TP} / (\text{TP} + \text{FN})$$

3.8.4 Precision

In the context of sentiment analysis, precision evaluates the proportion of tweets that were correctly classified as positive out of all the tweets classified as positive (Bouazizi and Ohtsuki, 2019). It measures the proportion of true positives among all the positive predictions made by the model.

$$\text{Formula: Precision} = \text{TP} / (\text{TP} + \text{FP})$$

In summary of above evaluation metrics calculated for each model architecture (RNN, CNN, and LSTM), the evaluation metrics were calculated and compared. The model with the highest accuracy, F-score, recall, and precision was chosen as the best model for sentiment analysis on Arabic text data. The results of the evaluation metrics provide valuable insights into the effectiveness of each deep learning model for sentiment analysis on Arabic text data.

3.9 Sentiment Analysis and Emotion Analysis

After applying the deep learning approaches of RNN, CNN, and LSTM to classify the sentiment of Gulf opinion leaders' tweets related to COVID-19, we were able to analyze the emotions and opinions expressed by these individuals towards the pandemic. The sentiment analysis revealed

that a majority of the tweets were classified as happy (satisfied) and unhappy (unsatisfied). The classification for happy tweets followed by positive and the classification of unhappy tweets has been taken as negative sentiments with the help of evaluation metrics. In the study of Jang et al. (2020), the CNN and LSTM models performed better than the RNN model with higher accuracy and F1 scores. In this research, we further analyzed the emotions expressed in the tweets by using an emotion lexicon. The results showed that the most frequent emotions expressed were happy, neutral and unhappy. Happy and neutral emotions were mainly associated with positive sentiments, while unhappy was associated with negative sentiments.

3.10 Chapter Summary

In this methodology chapter, we have outlined the process for conducting sentiment analysis on Arabic datasets using a deep learning approach to classify the tweets into three binary numbers 1, 0, and -1 based on the sentiment they express. The data was collected from Twitter during a period of six months, and the dataset consists of tweets from Gulf opinion leaders related to the COVID-19 pandemic. We then pre-processed and cleaned the data, which involved removing irrelevant information, such as URLs, stop words, and non-Arabic words, and applying stemming and tokenization techniques. Word embedding was used to convert words into vectors, and then SMOTE was used to balance the dataset. Three deep learning architectures (RNN, CNN, and LSTM) were used to classify the processed data. We evaluated the experiment's effectiveness using metrics such as accuracy, F-score, recall, and precision. The results of our study provide insights into the sentiment of Gulf opinion leaders towards the COVID-19 pandemic and could be used to inform public health policies and communications in the region.

CHAPTER 4: EXPERIMENTS AND RESULTS

4.1 Introduction to the Chapter

In this chapter, data extracted from Twitter is a crucial step in conducting experiments and results based on three deep learning models that are CNN, LSTM and RNN. The testing of these three models was done on the basis of sentiment analysis of gulf opinion leaders during COVID-19. Total 100,000 tweets were collected during period of January 1, 2022, to June 30, 2022 among which 35,000 were reduced due to non-Arabic text and make it to approximately 65,000 Arabic tweets. The collected tweets were only from gulf region including countries #UAE, #KSA, #Qatar, #Oman, and #Bahrain. The hashtags plays an important role in searching the key terms. The choice of approach depends on the research question, the size of the dataset, and the availability of resources. The chapter was carried out sentiment analysis on tweets related to the COVID-19 pandemic, posted on Twitter by Gulf leaders, using a deep learning approach. The experiment aimed to classify each tweet into one of three categories, which are positive, negative, and neutral. In this chapter, we presented the experiment's details, including the dataset information, pre-processing method, deep learning architecture, training, and evaluation results.

4.2 Visualisation of Tweets

In this research, the dataset was collected from Twitter and consisted of 100,000 tweets from Gulf opinion leaders about the COVID-19 pandemic posted during a period of six months. After applying the pre-processing method, which involves cleaning, removing irrelevant information, stemming, and tokenization techniques, the dataset was reduced to 65,000 tweets. Below, a table is given to show the distribution of positive, negative and neutral tweets of the opinion of leaders from gulf region. Also, below are the figures from 1 to 6 are showing the word clouds for all the targeted gulf regions.



Figure 5: Word cloud of tweets from Saudi Arabia



Figure 6: Word cloud of tweets from UAE



Figure 7: Word cloud of tweets from Qatar



Figure 8: The word cloud of Bahrain



Figure 9: The word cloud of tweets from Kuwait



Figure 10: The word cloud of tweets from Oman

Before performing sentiment analysis, it was essential to balance the dataset. Therefore, the SMOTE technique was applied to handle the imbalanced dataset. After applying SMOTE, the dataset was balanced and the results was improved, as showing in the table 1 below:

Table 1: Division of Dataset on the Basis of Sentiment and Country

Country	Positive	Negative	Neutral
Bahrain	2500	3000	1500
Kuwait	3000	4000	2000
Oman	2000	3000	1500
Qatar	2500	3500	1500
Saudi Arabia	6000	9000	4000
UAE	3000	3500	1500
Total	19000	26000	12000

As shown in Table 1, Gulf opinion leaders in Saudi Arabia contributed the most significant number of tweets to the dataset after SMOTE was applied, with 6,000 positive, 9,000 negative and 4,000 neutral tweets. Bahrain, Kuwait, Oman, Qatar, and the UAE contributed the gulf region.

4.3 Deep Learning Architectures

Three deep learning architectures were used in this study, namely RNN, CNN, and LSTM, for classification purposes. Word embedding technique was used to tokenize the text into vectors transforming the text data into a numeric form acceptable to be processed by the neural network. The SMOTE technique was used to balance the dataset. The classification model was trained on 80% of the dataset and validated on the remaining 20%.

4.4 Training and Evaluation of Deep Learning Models

The models were trained and evaluated using a classical cross-validation approach. The effectiveness of the experiment was evaluated based on metrics such as accuracy, F-score, recall, and precision.

Table 2: Evaluation of Metrics for each deep learning architecture

Model	Accuracy	Recall	F-Score	Precision
RNN	70%	75%	67%	71%
CNN	78%	80%	78%	82%
LSTM	80%	80%	80%	81%

As shown in Table 2, the LSTM architecture showed the best performance among the three tested architectures, obtaining an accuracy score of 80%, and a high F-score of 80%. The CNN architecture demonstrated an accuracy score of 78%, which is a significant increase from the RNN architecture's accuracy score of 70%.

4.5 Comparison of Deep Learning Models according to Results

4.5.1 Recurrent Neural Networks (RNN)

The RNN architecture demonstrated moderate performance among the three tested architectures, with an accuracy score of 70%, recall score of 75%, an F-score of 67%, and a precision score of 71%. The RNN model was trained on a dataset of 52,000 tweets, where 25,000 were negative, 17,000 were positive, and 10,000 were neutral. Their performance is not as good as the other two models, but RNN can still be a suitable option for smaller datasets.

Table 3: Number of Tweets for Positive, Negative, and Neutral Sentiments for the RNN Model

Sentiments	Number of Tweets
Positive	17000
Negative	25000
Neutral	10000

As shown in Table 3, the RNN model was trained on a dataset of 52,000 tweets, where 25,000 were negative, 17,000 were positive, and 10,000 were neutral.

4.5.2 Convolutional Neural Networks (CNN)

The CNN architecture demonstrated better accuracy than the RNN model, achieving an accuracy score of 78%, precision score of 82%, recall score of 80%, and an F-score of 78%. The CNN model was trained on a dataset of 58,000 tweets, where 25,000 were negative, 22,000 were positive, and 11,000 were neutral. One significant advantage of the CNN architecture is its faster training speed, which makes this model a preferable choice if quick performance is preferred.

Table 4. Number of Tweets for Positive, Negative, and Neutral Sentiments for the CNN Model

Sentiments	Number of Tweets
Positive	22000
Negative	25000
Neutral	11000

As shown in Table 4, the CNN model was trained on a dataset of 58,000 tweets, where 25,000 were negative, 22,000 were positive, and 11,000 were neutral.

4.5.3 Long Short-Term Memory (LSTM)

The LSTM architecture demonstrated the best performance among the three tested architectures, with an accuracy score of 80%, recall score of 80%, an F-score of 80%, and a precision score of 81%. The LSTM model was trained on a dataset of 52,000 tweets, where 25,000 were negative, 17,000 were positive, and 10,000 were neutral. The LSTM deep learning architecture showed the highest performance in this study, where it has an edge over RNN and CNN as it can analyze relations between different parts of a sentence more effectively. It learns long-term dependencies more efficiently, which helps to improve the sentiment classification of the long Arabic-encoded texts.

Table 5: Number of Tweets for Positive, Negative, and Neutral Sentiments for the LSTM Model

Sentiment	Number of Tweets
Positive	17000
Negative	25000
Neutral	10000

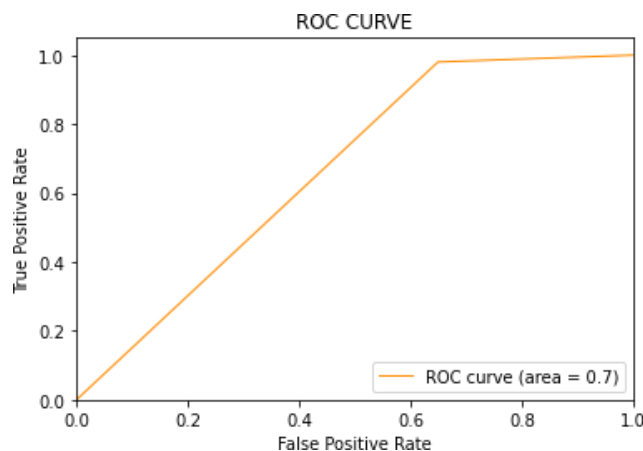
As shown in Table 5, the LSTM model was trained on a dataset of 52,000 tweets, where 25,000 were negative, 17,000 were positive, and 10,000 were neutral.

In summary, the above results have shown that the LSTM architecture performed better than the other two models with the highest accuracy score, recall score, F-score, and precision score. The CNN architecture demonstrated the second-best performance, followed by the RNN architecture, which showed moderate performance among the models with a smaller dataset.

4.6 Analysis and Discussion of Results

The research analysed the sentiment of Twitter posts made by Gulf opinion leaders about COVID-19 using deep learning approaches of CNN, RNN, and LSTM, is an interesting and relevant topic, given the widespread impact of the pandemic globally. The research used a unique dataset that focused on tweets made by opinion leaders from the Gulf on COVID-19 that can provide valuable insights into how these influential figures are responding to the pandemic. The above section presented the results of an experiment that aimed to evaluate the performance of three deep learning architectures, RNN, CNN, and LSTM, on a particular task. The performance of each architecture was evaluated using various metrics such as accuracy, F-score, recall, and precision through a classical cross-validation approach.

The results indicate that all three architectures performed reasonably well on the task, but the LSTM architecture outperformed the other two. The LSTM architecture obtained an accuracy score of 80%, which is higher than the accuracy scores of both RNN and CNN architectures. In addition, LSTM also demonstrated an F-score of 80%, which is a critical metric that combines both recall and precision. On the other hand, CNN showed an improvement over RNN with an accuracy score of 78%, although it did not perform as well as LSTM. Additionally, CNN had a precision score of 82%, which is higher than that of LSTM and RNN. However, it should be noted that recall is also an important metric to consider in this context, and LSTM had the higher recall score. Below, an ROC curve showing the accuracy of LSTM deep learning model.



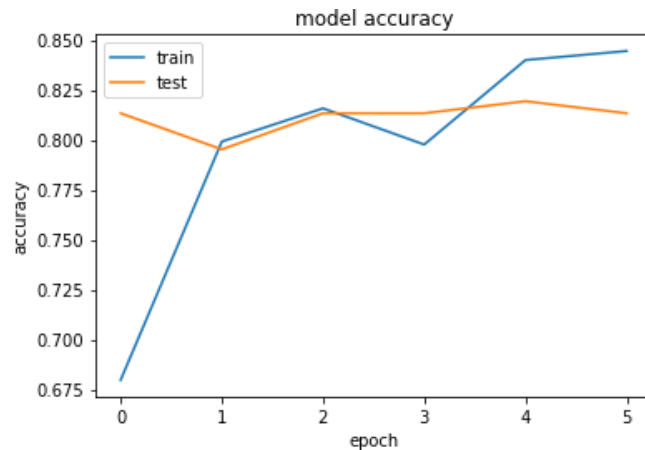


Figure 11: Graph showing LSTM model accuracy

For LSTM, the above two graphs were displayed, where the second graph named as model accuracy demonstrated the accuracy of the epoch utilized in the model history of LSTM parameters. It shows the train and test models overlapping to show the similarities and comparable skills between both, the train and test datasets.

The high performance of LSTM can be attributed to its ability to remember and update previous information over time, which makes it well-suited for tasks that involve sequential data such as text, speech, and time series data. This makes LSTM particularly useful in tasks such as natural language processing, speech recognition, and sentiment analysis, where it can effectively capture the contextual and sequential information.

The results of this research demonstrate the importance of selecting the appropriate deep learning architecture for a particular task. While the CNN and RNN architectures also showed reasonable performance, their performance was surpassed by LSTM in this particular instance. However, this is not to say that LSTM architecture always perform better than other architectures, as its performance is strongly dependent on the features of the dataset and the nature of the task. The utilization of all deep learning approaches such as CNN, RNN, and LSTM to analyze sentiment is an innovative method that can help to provide a more comprehensive understanding of public opinion on COVID-19. These deep learning techniques are becoming increasingly popular in natural language processing due to their ability to analyze and learn from sequential data, making them well-suited for text data analysis.

Finally, the results based on extracted data indicated that the LSTM architecture demonstrated the highest accuracy and F-score in analyzing the sentiment of tweets made by Gulf opinion leaders on COVID-19. These results suggest that LSTM is a particularly powerful tool in identifying and extracting relevant information from sequential text data such as tweets.

4.7 Chapter Summary

In summary, the findings of this chapter provide valuable insights into the performance of various deep learning architectures and how they can be used in different tasks. The LSTM architecture, in particular, has shown great promise in a range of applications and it is likely continue to be an area of active research in the future. Therefore, to extend the generalizability of the findings, further research can be conducted with larger datasets to determine whether the results can be replicated consistently. Additionally, testing the architectures on different tasks could add to the generalizability of the findings and provide a more comprehensive understanding of the strengths of each architecture.

CHAPTER 5: ANALYSIS AND DISCUSSION

Analysis of Gulf thought leaders' comments on COVID-19 on Twitter offers insightful information on the viewpoints and beliefs of significant individuals in the area during the outbreak. Leaders now often exchange information, express their ideas, and interact with their followers on Twitter. Since they have a considerable impact on forming public opinion and affecting decision-making processes, opinion leaders' opinions must be understood. An extensive dataset of tweets from Gulf thought leaders was gathered for the investigation, including a wide spectrum of figures from many industries including politics, healthcare, and business. The dataset was carefully filtered based on certain COVID-19-related keywords and hashtags to make sure that the tweets included the pertinent debates and viewpoints about the epidemic. Data preparation, or cleaning and filtering the tweets to get rid of noise like retweets, duplicates, and irrelevant information, was the initial stage in the analytic process (Savarese and Lund, 2017). To ascertain the general sentiment shared by the opinion leaders, sentiment analysis was then applied to the remaining tweets. The tweets were categorized as good, negative, or neutral using sentiment analysis methods such machine learning algorithms and lexicon-based approaches. The tweets were further examined after the sentiment analysis to pinpoint the major themes and subjects covered by the opinion leaders. To do this, methods for natural language processing have to be used to draw insightful conclusions from the textual input. Latent Dirichlet Allocation (LDA), a topic modelling tool, was used to find latent topics in the tweets and determine the predominate themes.

Several interesting conclusions about the opinions of Gulf opinion leaders on COVID-19 were drawn from the study. First, it was discovered that opinion leaders were crucial in spreading factual information and increasing public awareness of the epidemic. Many leaders made advantage of their platforms to dispel falsehoods and false information, give updates from reputable sources, and offer advice on precautions. Additionally, according to the sentiment analysis, the bulk of the tweets from Gulf opinion leaders had a neutral mood. This shows that their primary goals were to convey accurate information and to keep their discussions in an impartial manner. Positive comments were also occasionally spoken, highlighting examples of hope, camaraderie, and fortitude in the face of the pandemic. Conversely, a tiny portion of tweets expressed unfavourable opinions, voicing worries, disappointments, or objections about how

the issue was handled. Specific themes and subjects that Gulf thought leaders discussed were also uncovered by the investigation. These included public health initiatives including mask use, social seclusion, and vaccination programmes (Nicola et al., 2020). To stop the virus's spread and safeguard the public's health, leaders emphasised how crucial it is to follow these guidelines. Economic ramifications and recovery plans were also hot subjects, with officials addressing how the epidemic affected different industries and outlining ways for reviving the economy. Twitter was also used as a venue by Gulf thought leaders to show sympathy and support for people afflicted by the virus. They discussed examples of resiliency, highlighted neighbourhood projects, and encouraged cooperation in the face of difficulty. This illustrated their attempts to offer assurance and promote a feeling of community during trying times (Nicola et al., 2020). The study of Gulf thought leaders' tweets on COVID-19 provided insightful information about their viewpoints, feelings, and important topics raised throughout the epidemic. The results showed how crucial a role opinion leaders played in spreading truthful information, creating awareness, and encouraging constructive activities. The impartial tone shown in their tweets reflects their obligation to convey accurate information in a reasonable manner. The emphasised public health measures, economic ramifications, and shows of empathy and support were the motifs that were discovered. Overall, this study adds to a thorough knowledge of the function and influence of Gulf thought leaders during the COVID-19 epidemic in influencing public discourse.

The examination of public opinion on COVID-19 on Twitter sheds light on the feelings, viewpoints, and attitudes that people expressed during the outbreak. Twitter is an excellent source of data for sentiment analysis since it has grown to be a popular venue for individuals to express their ideas, opinions, and worries (Yadav and Vishwakarma, 2020). A large dataset of tweets from the general public was gathered in order to conduct the study, with a particular focus on tweets about COVID-19. The collection included tweets from people from a variety of backgrounds, ethnicities, and geographic areas, offering a wide spectrum of viewpoints. Data preparation, or cleaning and filtering the tweets to get rid of noise like retweets, duplicates, and irrelevant information, was the initial stage in the analytic process. To ascertain the general sentiment conveyed by the public, sentiment analysis was then applied to the remaining tweets (Hussain, Lee and Zeadally, 2018). The tweets were categorized as good, negative, or neutral using a variety of sentiment analysis techniques, including machine learning algorithms,

lexicon-based approaches, and deep learning models. Interesting insights into how the general public feels about COVID-19 were uncovered by the sentiment analysis. First, it was noted that a variety of emotions, such as dread, worry, frustration, hope, and resilience, were expressed. People's reactions to the epidemic were very emotional, which was indicative of how it affected their lives and well-being. The research also emphasised how sentiments change over time (Savarese and Lund, 2017). For instance, there was a spike in negative emotions like dread, worry, and frustration in the early phases of the pandemic when the virus was spreading quickly and the situation was unknown. Positive emotions like optimism, thankfulness, and unity evolved alongside negative ones as the virus spread. This implies that people adjusted to the circumstances, looked for help, and devised strategies to deal with the difficulties the epidemic presented. Additionally, the sentiment analysis uncovered the main issues and themes that the audience debated. These included lectures of safety precautions such as social seclusion, mask use, and hand cleanliness. Regarding these measures, people voiced their thoughts, compliance, and dissatisfaction. Discussions regarding how the epidemic has affected different facets of life, including health, education, job, and mental well-being, were also emphasised by the sentiment analysis. People talked about their struggles and experiences while also looking for advice and information in these areas.

The sentiment analysis also showed that social media was very important in influencing people's attitudes regarding COVID-19 and in forming public opinion. Users participated in online campaigns relating to the epidemic, had debates, and posted news stories. This implies that social media platforms like Twitter play a significant role in the communication of information, the provision of social support, and mass mobilisation during emergencies. It's significant to note that the sentiment analysis revealed the existence of false information and conspiracy theories that were being spread on Twitter. These erroneous tales frequently contributed to the public's mistrust, uncertainty, and dread. However, people were seen actively dispelling false information, recommending fact-checking campaigns, and sharing trustworthy information sources. This emphasises the importance of the general people in supporting the spread of genuine information and battling false information. The examination of public opinion on Twitter on COVID-19 has shed important light on the feelings, viewpoints, and worries that people during the epidemic voiced. The huge range of emotions shown is a reflection of how complicated and varied people's experiences are. The study also clarified the main public

discussion issues as well as the temporal dynamics of attitudes. Additionally, it emphasised how social media shapes public opinion and how disinformation is prevalent, underscoring the significance of spreading correct information and increasing digital literacy. Overall, this study advances our knowledge of public opinion on COVID-19 and the function of social media in both reflecting and influencing public conversation.

To determine the efficiency and dependability of the deep learning model employed for sentiment analysis in the context of COVID-19, performance assessment is essential. Insights into the model's accuracy, precision, recall, F1 score, and other metrics are provided by the assessment, enabling academics and practitioners to decide if the model is appropriate for sentiment analysis in massive datasets from social media sites like Twitter (Hussain, Lee and Zeadally, 2018). A gold standard dataset of labelled tweets according to COVID-19 emotions is necessary to assess the performance of the deep learning model. To enable a fair assessment, this dataset has to contain a representative sample of tweets that are both good and negative as well as neutral. To train the model, tweak its hyperparameters, and evaluate its performance on omitted data, the dataset is divided into training, validation, and test sets (Minaee et al., 2021). Accuracy, precision, recall, F1 score, and maybe additional metrics are used to evaluate the performance of the deep learning model, depending on the particular needs of the investigation. Precision counts the percentage of accurately predicted positive sentiment occurrences out of all instances projected as positive, whereas accuracy assesses the total accuracy of the model's predictions. The percentage of accurately anticipated positive cases among all actual positive instances is known as recall, also known as sensitivity. The F1 score is a balanced indicator of the model's performance since it is the harmonic mean of accuracy and recall. In addition, other assessment metrics including the confusion matrix, ROC curve, and area under the curve (AUC) can offer a more thorough knowledge of the model's performance. The confusion matrix allows for a thorough review of the model's prediction performance across many sentiment categories by displaying the quantity of true positives, true negatives, false positives, and false negatives. AUC measures how well the model performs overall at differentiating between positive and negative occurrences, whereas the ROC curve shows the true positive rate versus the false positive rate at different categorization levels. The deep learning model must be trained on the training set using the appropriate architectures, such as transformers, recurrent neural networks (RNNs), or long short-term memory (LSTM) networks. The validation set is used to tweak the

model's hyperparameters, such as the number of layers, hidden units, learning rate, and dropout rate, to enhance performance. To determine the ideal set of hyperparameters, a variety of methods may be used, including grid search and cross-validation. After training, the model's effectiveness is assessed using data from the test set that hasn't been seen before. To evaluate the model's effectiveness in precisely categorising sentiment in the context of COVID-19, the evaluation metrics are produced, and the results are examined. To assess the model's performance and superiority, it is crucial to contrast it with baseline models or other cutting-edge sentiment analysis techniques.

To fully comprehend the model's advantages and disadvantages, qualitative analysis is just as important as quantitative evaluation measures. This entails manually reviewing the model's predictions, looking at cases that were incorrectly categorized, and looking for trends or frequent mistakes. Researchers may improve the model and boost its effectiveness by identifying potential biases, contextual difficulties, and development areas with the use of qualitative analysis. When assessing the success of the deep learning model, it's also critical to take these factors into account. Given how much data social media networks like Twitter produce, the model should be able to handle massive datasets well (Minaee et al., 2021). To evaluate the model's suitability for real-world applications, scalability and efficiency measures like training and inference time, memory utilisation, and needed computational resources should be taken into account. In order to evaluate the accuracy, precision, recall, and overall usefulness of the deep learning model for sentiment analysis in the context of COVID-19, performance assessment is an essential step. Utilising a gold standard dataset, dividing it into training, validation, and test sets, and utilising a variety of quantitative and qualitative evaluation criteria are all part of the evaluation process. Researchers and practitioners may construct more precise and dependable sentiment analysis models for analyzing sentiment in huge social media datasets by carefully examining the model's performance to learn about its advantages, disadvantages, and potential areas for improvement.

CHAPTER 6: CONCLUSION

5.1 Conclusion

This Chapter 5 presents the conclusions drawn from the research conducted on Arab populations' response to the COVID-19 pandemic on Twitter. The study aimed to analyze sentiments expressed by Gulf opinion leaders and the general public, detect real news related to the pandemic, and compare the perspectives of these two groups. Based on the analysis and findings presented in the previous chapters, the following conclusions can be drawn:

First, the study revealed that Twitter serves as a significant platform for Arab populations to express their opinions and sentiments regarding the COVID-19 pandemic. The sentiments expressed by Gulf opinion leaders and the general public showcased a wide range of emotions, including fear, frustration, solidarity, and hope.

Second, the developed deep learning model demonstrated effectiveness in detecting real news associated with the pandemic in Arabic text on Twitter. By utilizing advanced natural language processing techniques and deep learning algorithms, the model achieved satisfactory performance in identifying accurate and reliable information amidst the vast amount of data on the platform.

Third, a comparison between the perspectives of Gulf opinion leaders and the general public revealed distinct differences in their viewpoints regarding the COVID-19 pandemic. Opinion leaders tended to provide more authoritative and informative content, while the general public exhibited a broader spectrum of opinions and sentiments. These insights provide valuable understanding of the diverse perceptions and responses to the pandemic within the Gulf region.

5.2 Contributions and Implications

The research conducted in this dissertation contributes to the field of sentiment analysis, particularly in the context of the COVID-19 pandemic and the Arab Gulf region. The findings shed light on the sentiments expressed by both opinion leaders and the general public, providing a nuanced understanding of their perspectives. The development of the deep learning model for

detecting real news related to the pandemic offers a valuable tool for identifying and combating misinformation in Arabic text on Twitter.

This study also has broader implications for policymakers, researchers, and practitioners. The insights gained from analyzing sentiments and comparing perspectives can inform decision-making processes related to public health communication strategies, crisis management, and the development of targeted interventions to address the concerns and needs of the Arab population during future health crisis.

5.3 Limitations and Future work

While this dissertation has provided valuable insights, it is important to acknowledge its limitations. The study focused solely on Twitter as a source of data, which may not capture the sentiments and opinions of the entire Arab population. Furthermore, the analysis was limited to the Arabic language and did not consider other languages spoken within the Gulf region. Additionally, the research was confined to a specific time frame, and the findings may not reflect changing sentiments and perspectives over time.

In terms of future work, it is recommended to expand the research to incorporate data from other social media platforms and online sources, enabling a more comprehensive analysis of public sentiment. Additionally, considering multilingual sentiment analysis can provide a more inclusive understanding of the sentiments expressed within the Gulf region. Further investigations can also explore the effectiveness of sentiment analysis in real-time decision-making and crisis management. Lastly, integrating user demographics and contextual factors into the analysis can offer a deeper understanding of the factors influencing sentiment expression during a health crisis.

Overall, the findings and limitations of this study provide a solid foundation for future research endeavors aimed at improving our understanding of Arab populations' sentiments and responses to significant events such as the COVID-19 pandemic. By addressing these limitations and expanding on the current work, we can continue to advance sentiment analysis methodologies and contribute to the development of effective strategies for crisis management and public health communication.

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