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Examining sentiment polarity regarding covid-19 on social media: harnessing, and decision support systems

Shobhit Srivastava[1],
[1,3]Department Of Computer Science & Engineering, University of Engineering & Management, Jaipur, Rajasthan 302004, India

Dr.Chinmay Chakraborty [2],
[2]Birla Institute of Technology, Mesra, Jharkhand 814142, India

Dr.Mrinal Kanti Sarkar [3]
[1,3]Department Of Computer Science & Engineering, University of Engineering & Management, Jaipur, Rajasthan 302004, India

**Corresponding Author: Shobhit Srivastava*
Email: shobhitan@gmail.com

Abstract:

Social media, designed for online interaction, enables rapid sharing of content via electronic means. Platforms like Twitter offer a space for individuals to openly express their opinions, which can then be shared further. The recent COVID-19 pandemic showcased the valuable insights gained from analyzing public sentiment, aiding in crafting effective public health responses. Concurrently, the dissemination of false information, fueled by social media and digital platforms, has emerged as a more significant threat to global public health than the virus itself, as evident from the pandemic. Analyzing articulated messages on Twitter can unveil the public's perspective on practices like social distancing, a process known as sentiment analysis. In this study, we employed multiple evaluation processes, considering various key points such as data collection sources, dataset size, and the sentiment analysis algorithm employed. Our research is distinctive in several ways, as it includes an examination of the impact of COVID-19 on individuals such as the working class, infected individuals, and field workers. The objective of this review article is to highlight the research methods employed for analyzing COVID-19 data and its social impact on people. We aim to review and analyze public sentiments towards social distancing, as expressed in the available COVID-19 data. Decision support systems (DSS) are becoming more and more important to how organizations run on a regular basis. An essential component of this is the storage of data, which offers an architecture that enables firms to extract, purify, and store enormous amounts of data. A data warehouse's primary goal is to arm knowledge workers with the knowledge they need to make decisions that are supported by reliable evidence.

Our research will utilize various resources, including libraries, books, electronic sources, and Google Scholar.

Approach: This study analyzed social media sentiments associated with social distancing during the COVID-19 pandemic, using relevant papers and the findings of different authors and researchers in the field. To ascertain the social network of predominate subjects as well as whether the tweets showed favorable, neutral, or negative attitudes, social network and sentiment analyses were also carried out.

Keywords:

COVID-19, social media, Sentiment analysis, Performance evaluation, Data Mining, Web Mining, Tweet Analysis, Behavioral analysis, Infodemic.

1. Introduction:

The SARS virus was initially identified in China in 2003. This virus had limited infection and was mostly confined to China. However, in later years, the SARS virus underwent multiple mutations, giving rise to a new virus belonging to the SARS family. This new virus emerged in China in late 2018 and in India in early 2019. It is derived from SARS-CoV-2 and has resulted in over a trillion confirmed cases and millions of casualties, placing a severe burden on the healthcare systems of many countries. The World Health Organization (WHO) has confirmed 336,790,193 cases to date, and the statistics indicate a global threat in terms of case numbers and casualties. The recorded information is utilized concurrently, and the availability of data enables scientists to make better decisions and draw conclusions (Pan et al., 2020). Undoubtedly, one of the most critical challenges in the battle against the COVID-19 pandemic is making accurate and timely decisions for the right reasons. Decision-makers at all levels, whether at the fundamental, decisive, or operational level, across various sectors such as government, public services, healthcare, social care, and businesses, are struggling to make effective and timely choices. Many managers and leaders face criticism due to poor decision-making, resulting in avoidable loss of lives and financial consequences. Given this scenario, leveraging technology, particularly artificial intelligence (AI), to assist decision-makers in making the most optimal and efficient judgments during this unprecedented situation has become increasingly crucial.

From a decision-making perspective, this section aims to analyze and underscore the impact of the COVID-19 pandemic on both research and practical implementation of AI in the field of information management. Recent research and guidelines from reputable institutions indicate that the mental health of patients is as important as their physical health. A positive mindset among infected individuals and frontline workers can significantly help mitigate the ongoing situation. Studies have shown that multidimensional healthcare interventions such as Ayurveda, Yoga, and meditation align with the recommended WHO treatment protocol. However, psychological studies of previous infection outbreaks, such as the severe acute respiratory syndrome (SARS) which is similar to the current SARS-CoV-2 pandemic, have revealed severe emotional and psychological burdens on healthcare workers and the general population, including sarcasm, anxiety, depression, and psychotic symptoms. As new application domains become available due to artificial intelligence's (AI) capacity to overcome some of the computationally demanding, intellectual, and even creative constraints of humans AI has been touted as a technology that can carry out jobs not just as well as humans can, but even greater. It is asserted that AI has the power to greatly enhance decision-making, arrive at better decisions, strengthen our capacity for analysis and judgment, and increase our capacity for innovation. There are numerous prospects for utilizing AI while the COVID -19 epidemic is plaguing the planet and the situation is getting worse every day. Information on the use and effects of AI during the global epidemic, yet, seems to be scarce. Understanding the mental impact on different populations and countries can provide a theoretical basis for identifying those at high risk and designing interventions, as well as resource planning and the implementation of public and government policies, which are of fundamental importance and have implications for the general public. Hence, we conducted the present systematic review and meta-analysis to assess the updated mental and psychological impact of the COVID-19 pandemic among healthcare professionals, the general population, and individuals with previous cases or COVID-19.

As the number of COVID-19 cases continues to rise rapidly in many countries, mental health issues have affected and will continue to affect a significant number of people worldwide. Understanding the thoughts and opinions of different populations and countries is crucial for identifying individuals at high risk, planning interventions, and making informed decisions at a global level. Therefore, we conducted the present systematic review and meta-analysis to assess the updated mental and psychological impact of the COVID-19 pandemic among healthcare professionals, the general population, and individuals with previous cases or COVID-19. The various mutations in the virus and the impact of vaccines also strongly influence people's psychological outlook. Interactive, computer-based decision support systems, often known as DSS, are designed to assist decision makers in resolving a variety of semi- to ill-structured problems involving multiple characteristics, objectives, and goals. The daily operations of businesses depend more and more on decision support systems. Organizations can now give the key personnel in the company access to necessary information and the means to use that information in a decision-support context thanks to the development of enterprise network computing, client/server architecture, and several important fresh data processing concepts. Social media has become the primary platform for expressing multiple emotions related to daily life. The current generation is highly active on platforms like Facebook, Instagram, and Twitter, and social trends play a significant role in extracting data for analysis. Our primary source of data is social media sites, from which we manually or programmatically extract valuable information. Our secondary sources of information are publicly available data pieces on different platforms, which are time-bound and specific to certain objectives. We closely monitor SCOPUS, SCIE, ELSEVIER, PubMed, and the daily activities of the WHO COVID-19 database (World Health Organization, 2020) for up-to-date and reliable data. Social media platforms provide more available data than ever before, making them current and reliable sources for obtaining this information. This paper primarily consists of a review of various papers that analyze COVID-19 factors based on data analysis (Xiang et al., 2020; Wu et al., 2009). The factors examined include patient behavior during COVID-19, the psychological impact after recovering from COVID-19, the impact on healthcare workers, the influence of different waves/variants, the effects of vaccines on the pandemic, and the status of different vaccines, among others.

1.1. Social media text and sentiment analysis: common behavior:

The use of social media platforms like Twitter and e-commerce platforms such as Amazon and Flipkart has resulted in the rapid creation of a significant amount of unstructured data. According to IDC, approximately 90% of the data generated today is unstructured. This abundance of unstructured data poses a challenge for industries and organizations when it comes to analyzing and extracting valuable insights from it. Unstructured data is created by humans in various forms such as reviews, blogs, forums, photos, videos, and other types of media. Reviews, for example, can cover a wide range of topics, including products, movies, vacations, and hotel services. Many companies are now leveraging internet reviews, ratings, and opinions to promote their products or services and identify potential issues in order to maintain their market reputation. We contend that the knowledge store described here offers a new and evolving future for the DSS in the following ten years, just as the introduction of data centers ten years ago marked a new direction for the DSS. This new course is based on the DSS's increased mission. That is the DSS's goal in terms of knowledge enhancement, or improved learning. This grew definition of a DSS also implies that, in the future, the effectiveness of each DSS will be assessed based on how well it advances and enhances knowledge, how well it increases the decision-maker(s)' mental models and comprehension, and how well it raises his or her decision-making. Sentiment analysis is becoming increasingly popular as businesses seek to better understand consumer feedback, automate noise filtering, and identify relevant content for decision-making purposes. One of the key challenges in this field is sentiment classification, which involves determining the judgment, mood, or evaluation of an object (such as a film, book, or product) or a specific aspect that can be categorized as positive or negative. Machine learning algorithms or lexicon-based approaches can be employed to analyze social media data and discern people's sentiments towards it. It is important to note that this study focuses on the sentiment analysis techniques utilized by various authors and is not limited to a specific geographical or demographic context. The study encompasses diverse techniques and considers datasets of all types, even if sentiment analysis is often conducted within specific regions or with specific groups of people.

2. Preliminary study:

The world is currently facing a microscopic enemy known as COVID-19, and government strategies are constantly adapting to the behavior of different variants of the virus. Variants such as ALPHA, DELTA, OMICRON, NEOCOV, DELMICRON, and others exist, each with varying infection rates and infection mortality rates. People's behavior towards the disease changes as the severity of the situation changes. The virus continues to spread rapidly daily, and there is a constant concern about the emergence of a more lethal variant with a rapid increase in mortality and infection rates. Various disease management strategies have an impact on human psychology and mental health. Nowadays, data analysis plays a significant role in shaping people's mindsets. People frequently turn to the media as a source of current information to help them make informed decisions about their personal health issues. This may be especially true in the case of the COVID-19 pandemic due to the volume of data. Major uncertainties about viral propagation, post-recovery immunity, and medication therapy persist with daily information. Many people look to social media for explanation of what may appear to be an overload of information.

Ordinary citizens now examine past patterns of information and form their perspectives based on that. Virtual entertainment and online entertainment platforms have experienced a tremendous surge in daily usage. Virtual entertainment has become increasingly relevant in people's lives, particularly among smartphone users. During lockdown or quarantine periods, physical movement in cities decreases while online traffic on social networking sites increases significantly. Nowadays, people tend to rely more on posts and tweets shared on social media platforms like Instagram, Facebook, and Twitter. It is fully justifiable to deploy cutting-edge predictive modeling and Explainable AI components that can model nonlinear trends in nonparametric setups. AI has proven to be quite adept at identifying the hidden pattern of influence of selected distinct characteristics. The frameworks are categorized as instruments for trading based on the level of precision attained. It is simple to expand the frameworks to evaluate volatility in other significant assets. It is expected that posts shared through online entertainment platforms should guide people to obtain accurate and reliable information. However, in many cases, the information circulated on virtual entertainment platforms has led people to make incorrect decisions, such as misleading COVID-19 data. When examining posts related to COVID-19, it is evident that misleading information and figures have deceived people. COVID-19 has already caused significant mental disruption, and the emotions and tweets surrounding it are disturbing, fueling fear and anxiety. It is essential to address the dissemination of deceptive information from various sources. The main focus of this paper is to urge individuals to refrain from posting information on online entertainment platforms that could ultimately undermine the effectiveness of crisis management. Individuals should take responsibility for sharing information that is beneficial to the general public. It is important to note that Twitter has become a us prominent platform for spreading COVID-19 news. In Table 1, we have presented average effective parameters that have been accepted by experts.

Information and sentiment analysis based on Twitter have become popular and easily analyzable. Researchers utilize Twitter data to gain insights into sentiments and conduct sentiment analysis. Specifically, researchers focus on analyzing sentiments in tweets using appropriate machine-learning methods. To address this, we formulate the first research question:

RQ 1: How can we analyze the behavioral aspects of tweets based on pre and post-COVID-19 symptoms?

To tackle this question, we gather information from tweets and employ preprocessing techniques to remove unreliable data and extract relevant information. We then categorize the tweets as positive or negative and apply feature extraction techniques to determine the precise dimensions of the data.

The second research question, RQ 2, comes into play:

RQ 2: How can we analyze the behavioral aspects of data extracted from multiple sources (e.g., Kaggle, WHO, CHIME) based on pre and post-COVID-19 symptoms?

In this category, we utilize various datasets available on platforms like Kaggle, WHO, CHIME, etc., to analyze the behavioral aspects of the data. We employ similar techniques used in RQ 1 to determine the behavioral dimensions.

In the third step, we combine the datasets used in RQ 1 and RQ 2, apply feature extraction, and analyze the behavioral aspects of the data.

Based on the solutions to the above research questions, we aim to achieve the following objectives:

- Understand the behavioral status of the dataset.

- Compare the behavioral aspects.

- Address fluctuations in behavioral patterns.

- Assist people with the analysis of upcoming pandemic waves.

In terms of data collection methods employed by authors, it is crucial to gather relevant and reliable data, as it forms the backbone of any study. Most researchers in sentiment analysis studies on COVID-19 collect data from Twitter, considering factors such as region, time, and spatial categories. Different data cleaning techniques and tools are utilized for data cleaning. This review article aims to cover all aspects of sentiment analysis related to COVID-19, including data collection and cleaning techniques and their impact on performance. DSS can further improve the tacit to explicit knowledge conversion by eliciting one or more "what-if" examples (also known as "model instances") that indicate scenarios that the knowledge worker wants to investigate. The knowledge worker is estimating ranges of those parameters/values that reflect the actual and/or possible decision-making environment depicted in the model as s/he modifies one or more model coefficients or right-hand side values (for example, in a linear programming model) to investigate its effect on the modeled solution. Which is, the knowledge worker is transforming the implicit knowledge of diverse historical circumstances and/or decisions into explicit knowledge that may be used to inform decision-making processing and collection, as noisy data (e.g., sarcastic or depressive) can be difficult to handle. Collecting user opinions on specific topics can be burdensome due to the vast amount of data available on social media platforms. Difficulties are also attributed to defining keywords to identify desired data. The data used in this paper comprises a collection of reviews from various domains, totaling over 5.1 million research reviews. These reviews are categorized into three major categories Library, book, electronic, and Google Scholar (Figure 1 (a)). Those online reviews were posted by over 3.2 million of reviewers. In review collection, we initiated to various domains such as ACM, IEEE explorer, Research gate, and Google Scholar (see figure 2.

Effective Parameters / **Author Name with year**	Social Bookmarking	Positive, Negative impacts	Even neutral	Social Bookmarking	Social media	Intelligent platform	Aggressive	accuracy
Siru Liu et. al. (2021)	√	√	√	√	√	√	√	√
F. M. Javed et. al. (2021)	√	√	√	√	√	√	√	√
Joanne Chen Lyu et. al. (2021)	√	√	√	√	√	√	√	√
Simranpreet Kaur et. al. (2020)	√	√	√	√	√	√	√	√
Amin Mahmoudi et. al. (2020)	√	√	√	√	×	√	√	√
Jolin Shaynn-Ly Kwan et. al. (2020)	√	√	√	√	√	√	√	√
Al-garadi et. al. (2016)	√	√	√	√	√	√	√	√
Alamoodi et. al. (2020)	√	×	√	√	√	√	√	√
Alamoodi et. al. (2019)	√	√	√	√	√	√	√	√
Aljuaid et. al. (2020)	√	√	√	√	√	√	×	√
Almazidy et. al. (2016)	√	√	√	×	√	√	√	√
Alwan et. al. (2020)	√	√	√	√	√	√	√	×
Chaudhary et. al. (2017)	×	√	√	√	×	√	√	√
Chung et. al. (2015)	√	√	√	√	√	√	√	√

Table 1: Boundaries acknowledged by specialists[6]

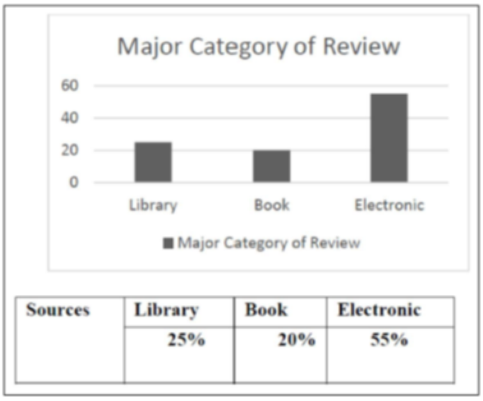


Fig. 1. Major category for Review

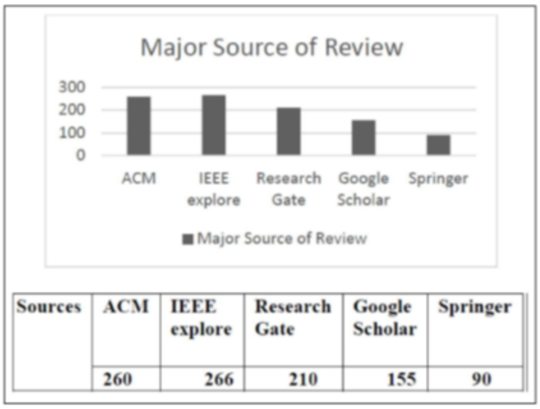


Fig. 2. Major source for Review

3. Resource center of sentiment analysis: social media perspective

Indeed, communication in today's world knows no boundaries. The internet has become faster and more powerful, with revolutions like 5G and IoT shaping our daily lives. This has led to significant changes, particularly in the realm of social media. In the past, data analysis was challenging due to the rigorous process of data collection when internet facilities were not as strong. However, with the advancements in internet technology, social media platforms have empowered people to freely express their views on various topics.

The internet's technological enhancements have made it easy to share small videos, pictures, texts, emoticons, and more on social media platforms. As a result, vast amounts of data are now freely available, and anyone can access and manipulate public sentiment. Among the social media platforms, Twitter has emerged as one of the most impactful platforms for both official and non-official data sources. We agree that social and statistical analysis can influence human behavior, especially when it comes to health-related issues. Social media platforms serve as potential data centers for big data, encompassing various types of data such as images, texts, short videos, and more. Online users extensively share their perspectives on every social trend, making it crucial to transform these insights and posts into valuable resources.

Analyzing patterns of tweeting on Twitter, as well as the responses, likes, and shares on Facebook, provides an understanding of user sentiments and their engagement levels. It reveals the social connections and openness of users in expressing emotions and opinions such as joy, sadness, anger, positivity, negativity, concern, shock, disgust, or confusion. This analysis can be conducted using massive amounts of tweets.

Large-scale extractions of behavioral datasets, including human emotions and sentiments from virtual entertainment networks, are crucial for understanding global public impacts, making informed business decisions, and policy development. Sentiment analysis and opinion mining have become valuable tools in various application domains such as tourism, business, education, and healthcare, serving different purposes.

3.1. Epidemic management:

Public authorities must take several steps to address an epidemic like this. Although preserving lives and providing for patients' needs remain of utmost importance, there are many different fronts in the war against the epidemic. The vital supply chain for medications, personal protective equipment (PPE), sanitizers, oxygen, ventilators and their parts, and all other necessary equipment must be managed by the public authority. The governing bodies additionally must make sure that there are enough ICU beds, quarantine facilities, and hospital beds available. Each of these tasks calls for an all-encompassing technological solution. Every step of the test sample collection process, including the testing, reporting, and follow-up intervention, calls for an established technology platform.

3.2. Knowledge management:

Knowledge management encompasses the conversion of tacit knowledge into explicit expertise, the filtering, storage, retrieval, and distribution of explicit knowledge, as well as the generation and validation of innovative information to enhance its practicality and usability. Tacit knowledge in this context comprises the ingrained beliefs, perspectives, and mental models that are often taken for granted by individuals. It also encompasses the subjective expertise, insights, and intuitions cultivated through extensive immersion in a specific activity or profession.

In contrast, explicit knowledge can be formalized using language, symbols, rules, objects, or equations, facilitating sharing with others. The process of articulation involves the transformation of implicit knowledge into explicit knowledge. Within the decision-making process, articulation can involve several actions, including, but not limited to:

1. Clearly defining the decision's objective, such as analyzing how warehouse quantities and locations impact supply costs in a new marketing area.
2. Articulating parameters, objective functions, relationships, and other elements within a decision support systems (DSS) mathematical model (i.e., model construction).
3. Formulating "what-if" scenarios in the model to represent current and potential decision-making situations.
4. Evaluating decision alternatives while considering the inherent uncertainty in decision-making.

By navigating these steps, knowledge management improves decision-making processes and enhances the effectiveness of utilizing both tacit and explicit knowledge.

4. Sentiment analysis:

Indeed, sentiment analysis plays a crucial role in analyzing public sentiment and sentiment orientation, particularly in the context of transmissible disease outbreaks. Information technologies and social media have facilitated a wide junction to understand and monitor such outbreaks. Researchers have utilized various datasets and searching methods to gain insights into public opinions towards different dimensions of disease outbreaks, which can have a significant impact on the industry and decision-making processes.

The importance of sentiment analysis becomes even more evident during global pandemics like COVID-19. By analyzing public sentiment, experts can gain valuable insights that can aid in controlling the spread of diseases more effectively. Understanding public opinions and emotions surrounding the pandemic is crucial for shaping appropriate strategies and interventions. COVID-19 remains a highly debated and discussed topic on social media platforms. Conducting sentiment analysis in the context of COVID-19 is of great importance given the recent events and the widespread impact of the virus. This review aims to examine the role of sentiment analysis in understanding the dynamics of COVID-19. It also seeks to identify and select relevant keywords for future research on COVID-19. Furthermore, sentiment analysis can shed light on the behavior and experiences of infected individuals and frontline workers who are actively involved in combating the virus. By analyzing their sentiments and opinions, valuable insights can be gained to improve support systems, address concerns, and enhance the overall response to the pandemic. Artificial intelligence (AI) can be effectively employed in the transfer of tacit knowledge between individuals through kinematic analysis of physical processes. This approach enhances the detection of rapid or subtle movements during the demonstration phase. Kinematics employs reflective dots and/or sensors strategically placed on various limbs and joints of the demonstrator. This setup enables the recognition of intricate actions, like finger twisting or transformations, as seen when a master chef kneads bread dough. Kinematics serves as a natural bridge for converting tacit knowledge into explicit knowledge. Once the process is recorded, it allows for a detailed examination of the relative motion of joints and appendages, facilitating a comprehensive understanding of the demonstrated procedure.Overall, sentiment analysis serves as a powerful tool to understand public sentiments, monitor the impact of disease outbreaks, and guide decision-making processes during pandemics like COVID-19. In figure 3, we have illustrates the process of sentiment analysis.

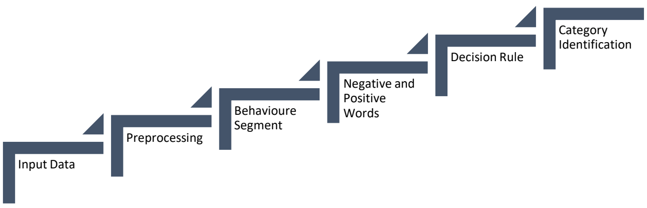


Figure. 3: Steps for sentiment analysis

4.1. Sentiment analysis strategies:

The role of sentiment analysis is to determine the subjectivity and polarity (positive, negative, or neutral) of a given text or phrase, which helps in understanding the opinion or sentiment of the opinion holder. Sentiment analysis involves using various natural language processing (NLP) techniques and machine learning algorithms to analyze and classify text data based on its sentiment.

The primary goal of sentiment analysis is to extract subjective information and determine the sentiment expressed in a piece of text, such as a review, social media post, or customer feedback. It aims to understand the emotions, attitudes, and opinions of individuals towards a particular topic, product, service, or event.

By analyzing sentiment, businesses and organizations can gain valuable insights into customer opinions, preferences, and satisfaction levels. Sentiment analysis can be used to monitor brand reputation, assess customer feedback, identify emerging trends, detect potential issues, and make data-driven decisions to improve products, services, and overall customer experience.

Sentiment analysis techniques can range from rule-based approaches that rely on predefined sentiment lexicons to more advanced methods such as machine learning algorithms that learn from labeled training data to classify sentiments. These techniques consider various linguistic features, context, and domain-specific knowledge to accurately classify the sentiment expressed in a text.

Overall, sentiment analysis plays a significant role in understanding and quantifying subjective opinions and sentiments, providing valuable insights for businesses, researchers, and decision-makers in various domains. The following levels are used for the analysis of the sentiment approaches (see fig. 4).

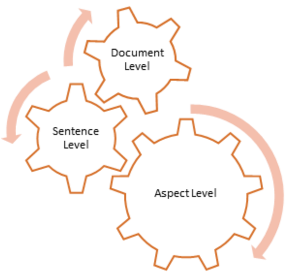


Figure. 4: Analysis category of sentiment

4.1.1. Document-level sentiment analysis:

In sentiment analysis, the document-level analysis refers to the classification of a single document or text as a whole based on the sentiment expressed by the opinion holder. The sentiment can be categorized as positive, negative, or neutral, depending on the overall expression or tone of the document. In document-level sentiment analysis, the focus is on analyzing the sentiment of the entire text, rather than examining individual opinions or aspects within the document. This approach is commonly used when the sentiment expressed in a document is relatively consistent throughout, and there is no need to delve into specific aspects or fine-grained details.

For example, if a customer writes a review about a product and the overall sentiment expressed in the review is positive, the document-level sentiment analysis would classify the entire review as positive. Similarly, if the sentiment expressed in the review is negative, the document-level sentiment analysis would classify the review as negative. In cases where the sentiment is neither predominantly positive nor negative, the document would be classified as neutral.

Document-level sentiment analysis is often used for tasks such as sentiment classification of customer reviews, analyzing the overall sentiment of social media posts or news articles, or determining the sentiment of feedback or survey responses. It is important to note that document-level sentiment analysis may not capture the nuanced opinions or different sentiments expressed towards specific aspects or entities within the text. For more granular analysis, aspect-based sentiment analysis or entity-level sentiment analysis may be employed to extract sentiment at a more detailed level.

Overall, document-level sentiment analysis provides a high-level understanding of the sentiment expressed in a document and helps in categorizing it as positive, negative, or neutral based on the overall opinion holder's expression.

4.1.2. Sentence level sentiment analysis:

To perform sentence-level sentiment analysis, the analysis is focused on individual sentences within a document rather than the document as a whole. This approach allows for a more fine-grained understanding of the sentiments expressed in each sentence. Sentence-level sentiment analysis involves analyzing the sentiment polarity (positive, negative, or neutral) of each sentence and can provide more detailed insights into the opinions expressed within a document. Face-to-face interaction cannot be replaced, which is why so many individuals are finding it difficult to do their business remotely during the pandemic. We acknowledge that technology can offer practical communication tools. From an organizational standpoint, it is crucial for managers of any homeworkers to understand that, even though they can take proactive steps to avoid feeling socially isolated, homeworkers still need opportunities for interaction with coworkers for both formal and informal information sharing and professional development. It's critical that businesses should not "forget" about their less visible employees or view them only as a means to an end. By examining each sentence separately, it becomes possible to capture varying sentiments and opinions that may exist within the overall document.

For example, consider the following sentence:

"I loved the movie, but the ending was disappointing."

In sentence-level sentiment analysis, this sentence would be analyzed as two separate statements:

1. "I loved the movie" - Positive sentiment

2. "The ending was disappointing" - Negative sentiment

By breaking down the sentence into individual statements, the sentiment analysis can capture the mixed sentiments expressed within the sentence.

Sentence-level sentiment analysis is useful when there is a need to understand the sentiment expressed at a more granular level, especially when different parts of a document convey contrasting opinions. It can be applied in various domains such as product reviews, social media posts, or customer feedback, where analyzing the sentiment at the sentence level provides a deeper understanding of the expressed opinions. It's important to note that sentence-level sentiment analysis may not capture the full context or meaning of a sentence, as sentiment can be influenced by the surrounding sentences or the overall document. Therefore, combining sentence-level analysis with document-level analysis can provide a more comprehensive understanding of the sentiment within a document.

4.1.3. Aspect level sentiment analysis:

Aspect-level sentiment analysis is a specialized method that concentrates on identifying and extracting particular elements or entities mentioned within a sentence or paragraph. This technique aims to ascertain the sentiment associated with each of these aspects individually. Such an approach enables a more precise and focused analysis of opinions and sentiments expressed in a given text, particularly with regard to various aspects under consideration. Aspect-level sentiment analysis consists of two main subtasks: Aspect Extraction: This involves identifying and extracting the aspects or entities mentioned in the text that opinions are expressed about. For example, in a restaurant review, the aspects could be food quality, service, ambiance, and price. Various techniques such as rule-based methods, named entity recognition, or machine learning approaches can be used to extract aspects from the text.

Sentiment Classification: After the aspects are successfully identified, the subsequent step involves sentiment classification, where the goal is to establish the sentiment polarity for each aspect. This classification process entails analyzing the opinions or sentiments expressed regarding each specific aspect, leading to the assignment of sentiment categories such as positive, negative, or neutral to each one. Machine learning algorithms such as CNN (Convolutional Neural Network), memory-based models, attention mechanisms, CRFs (Conditional Random Fields), or rule-based models can be employed for sentiment classification.

Aspect-level sentiment analysis models aim to establish the relationship between the opinion holder and the specific aspects being discussed. By identifying the aspects and determining the sentiment towards each aspect, this analysis provides a more detailed understanding of the sentiments expressed towards different elements in the text.

Regarding the employment of AI in battling pandemics, there have been several discussions, but it seems there are more questions than there are solutions. It is argued that AI has risen to the task of curing this horrible illness. There does not seem to be any information available about how AI is helping to control the COVID-19 outbreak. According to Grossman [2] "the first real test of AI in a crisis," the findings are conflicting. Although there are numerous individual applications that are helpful, the technology is still in its infancy and cannot deal with challenging public policy challenges. In terms of using the lessons from COVID-19 to make future decisions that will be better.

In Table. 2 and 3, the comments and contributions by experts likely provide insights into various approaches and techniques used for aspect-level sentiment analysis. These tables may present the opinions and suggestions of experts in the field, highlighting different methods, models, or frameworks that have been utilized in aspect-level sentiment analysis tasks.

Author Name	***Method Used***	***Analysis Area***	***Feature(s)***	***Dataset***	***Limitation***
Siru Liu et. al. [1], 2021	Valence Aware Dictionary and	Sentiment Analysis	Text Analysis	Twitter Dataset of 2678372 tweets.	Only Text-based analysis was used which was extracted by Twitter.

	Sentiment Reasoner				
Yejin Bang et. al. [2], 2021	BERT Method	Fake News Detection	Text Analysis	Fake News COVID-19 of 10700 social media posts. Tweets COVID-19 dataset	Comparative analysis with multiple methods is unavailable.
F. M. Javed Mehedi Shamrat, et. al. [3], 2021	Supervised KNN, KNN Classification	Sentiment Analysis using Natural Language Processing	Text Analysis	Twitter dataset of 87689 tweets.	Analysis of USA-based vaccines only. Lack of holistic approach.
Joanne Chen Lyu, et. al. [4],2021	Machine learning classifiers using Python Programming	Sentiment Analysis	Text Analysis	Twitter-based dataset of 1499421 tweets.	Textual data-based analysis
Nalini Chintalapudi, et. al. [5], 2021	SVM, Single layer LSTM	Sentiment Analysis using Deep Learning Models	Text Analysis	Twitter-based dataset of 3090 tweets extracted from Github.	Textual data-based analysis
Robert Marsec, et. al. [6], 2021	AFINN lexicon Kruskal Wallis Analysis tool Post hoc Games-Howell Test	Sentiment Analysis	Text Analysis	Twitter academic interface application used to extract a twitter-based dataset of 701901 tweets.	Lack of analysis of Indian vaccines and also lack of multiple features like Vaccine hit ratio.
Vedika Gupta, et. al. [7], 2021	Multimodel emotion care Scheme	Emotion Analysis	Text, Image	Twitter-based dataset of 884111 tweets of Text and Image.	Limited feature extraction-based analysis mostly on textual data.
SV Praveen, et. al. [8], 2021	Graph-based analysis	Sentiment Analysis	Text Analysis	Twitter-based dataset of 73760 tweets.	Only machine learning tools were applied. It could be better if Deep learning tools are also applied.
Wenhuan Zeng, et. al. [9], 2021	Machine learning techniques	Machine Learning and Deep Learning analysis based	Text, Image	WHO, medRxiv, bioRxiv, GISAID COVID-19 Dataset	Limited feature extraction-based analysis mostly on textual data.

		on Multimodel Dataset.			
Bangren Zhu, et. al. [10], 2020	LDA Method	Sentiment Analysis using Web Crawler	Text Analysis	WEIBO Dataset	Limited feature extraction-based analysis mostly on textual data.
Klafier Gracia, et. al. [11], 2021	Crystelfell and NLP tools.	Sentiment Analysis	Text Analysis	Multilingual Dataset of 3332565 English language tweets and 3155277 Portuguese tweets.	Limited feature extraction-based analysis mostly on textual data.
Simranpreet Kaur, et. al. [12], 2020	IBM Watson Tone Analyzer	Emotion Care	Text Analysis	16138 tweets dataset from Twitter.	Limited feature extraction-based analysis mostly on textual data.
Johnna Blair, et. al. [13], 2020	Traditional Sentiment Analysis methods use the collection, analysis, and prediction-based methods.	Mental Health Analysis	Text Analysis	Tweets-based dataset.	Limited feature extraction-based analysis mostly on textual data.
Amin Mahmoudi, et. al. [14], 2020	Feature Extractor	Behavior Analysis	Text Analysis	9457721 English Tweets Dataset	Limited feature extraction-based analysis mostly on textual data.
Mideth Abisado, et. al. [15], 2020	Multinomial Naive Bayes classification	Sentiment Analysis	Text Analysis	29514 tweet dataset of Twitter Data	Limited feature extraction-based analysis mostly on textual data.
Sreeramanna Aithal, et. al. [16], 2020	Naïve Bayes, K-Mean, Fuzzy C Mean, Hybrid Methods	Sentiment Analysis	Text Analysis	Text Blob dataset	Limited feature extraction-based analysis mostly on textual data.
Mauel E. Garcia,	R Statistical Software	Sentiment Analysis	Text analysis	Tweets-based dataset of almost	Limited feature extraction-based

et. al. [17], 2020				65213 multilingual, slang word tweets.	analysis mostly on textual data.
Jolin Shaynn-Ly Kwan et.al. [20],2021	Multiple Classifier-based analysis.	Sentiment Analysis	Text Analysis	Twitter-based dataset of 1056049 tweets of different countries.	Limited feature extraction-based analysis mostly on textual data.
Md Jamal Ansari, Electronic Journal of General Medicine	Naïve Bayes Classifier	Sentiment Analysis	Text Analysis	820000 worldwide twitter-based datasets.	Limited feature extraction-based analysis mostly on textual data.
Jolin Shaynn-Ly Kwan, et.al. [] 2020	EMOLEX, AFINN Lexicon	Sentiment Analysis	Text Analysis	896031 geospatial Twitter-based datasets.	Limited feature extraction-based analysis mostly on textual data.
Koyel Chakraborty,et.al. [], 2020	AFINN	Behavioral Analysis	Text Analysis	Twitter-based dataset of 1056049 tweets of different countries.	Limited feature extraction-based analysis mostly on textual data.

Table. 2: Experts comments and contributions research domain

Author Name	***Pre-Processing Technique***	***Model Employed***	***Performance Measures***
Siru Liu et.al. [1], 2021	Analysis of tweets using VADER tool which is a lexicon-based tool and generates F Score based on the sentiment type.	VADER tool is a Lexicon and rule-based analyzer.	To decide whether a huge change in feeling after some time existed, we utilized the Pruned Exact Linear Time (PELT) calculation, which applied a system that limited the expense capacity to observe change focuses. It has been displayed to make a significant improvement contrasted with different strategies, both in precision and speed.
Yejin Bang et.al. [2], 2021	Transformer-based language model with a feed-forward classifier.	Deep neural network-based Classifier, BERT Classifier, RoBERT Model	Cross entropy loss function is based on Kull-back Labeller divergence. SCE and GCE which are systematic cross-entropy and generalized cross-entropy uses to enhance the robustness of the noisy tweets.
F. M. Javed Mehedi Shamrat, et.al. [3], 2021	Natural Language Processing-based preprocessing. Tokenization, normalization, and lemmatization are three	NLP and Supervised KNN classification algorithm.	KNN Algorithm is used for accuracy measures.

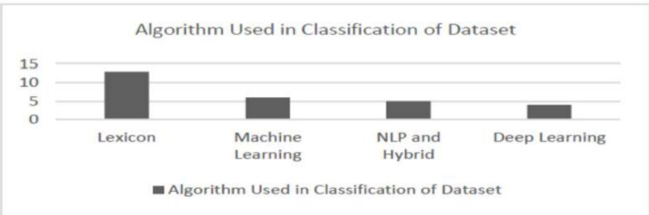
	major functions in natural language processing for preprocessing text.		
Joanne Chen Lyu, et.al. [4], 2021	Data extracted from Twitter and R Studio tool used to preprocess the data	Modeling is done using the K-mean clustering algorithm and LDA classification tool. textmineR package also used for Modelling. Sentiment and emotion analysis was done using the syuzhet package of R.	tweeternot, tidytext, and textstem packages of R have been used for accuracy.
Nalini Chintalapudi , et.al. [5], 2020	Data Extracted from Twitter and Github. Labeled the tweet sentiment with the tags like joy. sad, anger, fear, etc. manually.	BERT, LSTM is used for modeling the sentence and prediction of the next sentence.	BERT, LR, LSTM using advanced sigmoid function used for efficiency and accuracy consideration.
Robert Marsec, et.al. [6], 2021	Twitter academic API using R	AFINN Lexicon was used for the analysis of Twitter data.	Lexicon-based Twitter sentiment analysis serves as a sophisticated technique that enables real-time tracking of sentiment regarding endorsed COVID-19 vaccines. This approach facilitates the detection of significant events influencing sentiment both at a global scale and on a country-specific basis.
Vedika Gupta, et.al. [7], 2021	NRC Emotion Lexicon used for creating the emotion Score.	The fusion-based algorithm is based on the emotion score evaluated using NRC Emotion Lexicon.	NRC Emotion Lexicon
SV Praveen, et.al. [8], 2021	Python library “Twint” used for data extraction. In data preprocessing, they have removed the stop words, numbers, punctuations, and hyperlinks.In the wake of eliminating the prevent words from the corpus, we played out the most common way of stemming and lemmatizing to the information in our examination.	Latent Dirichlet Allocation	Probabilistic Latent Semantic indexing and BoW approach has been used for improving the performance.

Wenhuan Zeng, et.al. [9], 2021 2021	XGBoost, MLP, MAFFT	Multilayer Perceptron and Bidirectional LSTM	Receiver Operating Characteristic has been used for ensuring performance measures.
Bangren Zhu, et.al. [10], 2020	Data obtained from Quingbo Big Data Agency. The Jieba package of python is used to segment Weibo text.	LDA method	Python genism and Python regular Match.
Klafier Gracia, et.al. [11], 2021	LDA probability Distribution technique for preprocessing the data.	CrystalFeel emotion score technique. SpaCy for the Portuguese language. BERT/SBERT is used for sentence modulation.	A combination of different techniques used to assure performance and comparison of the performance metrics is also shown in the paper.
Simranpreet Kaur, et.al. [12], 2020	Data extraction from Twitter API. Preprocessing done using Text Blob.	IBM Watson Tone Analyzer	Data Visualization through WHO Datasets.
Johnna Blair, et.al. [13], 2020	Manual data collection and preprocessing of the tweets dataset.	Valence Aware Dictionary and sentiment reasoner tool used to analyze the tweets.	Valence Aware Dictionary and sentiment reasoner tool used to analyze the tweets.
Amin Mahmoudi, et.al. [14], 2020	Data were extracted from Twitter, Kaggle and preprocessed with traditional techniques.	Correlation coefficients like Spearman and Pearson.	Correlation coefficients like Spearman and Pearson.
Mideth Abisado, et.al. [15], 2020	Data collection from twitter the cleaning of the data by removing stop words, TD-IDF uses for feature extraction	Multinomial Naïve Bayes used for sentiment analysis process.	TD-IDF is used to improve performance.
Sreeramanna Aithal, et.al. [16], 2020	Data extraction from Twitter using Tweepy API. Removes all the other language tweets except English language tweets without any slang words.	Text Blob method used for polarity measures and Sentiment analysis.	Text Blob used for enhancing the performance.
Mauel E. Garcia, et.al. [17], 2020	Data extracted from Twitter using R. Manual data preprocessing like removal of stop words and other traditional	Lexicon-based analyzer used for sentiment analysis.	Multiple types of R packages like sentiment, rtweet, and tidytext are used to ensure high performance.

	preprocessing techniques.		
Jolin Shaynn-Ly Kwan et.al. [18],2021	Data extracted from Twitter API. Preprocessing is done using standard procedures.	AFINN Lexicon	NRC World Emotion Lexicon is used to improve performance.
Md Tarique Jamal Ansari et.al. [19], 2021,	Data extracted from Twitter API. Preprocessing is done using standard procedures.	Multinomial Naïve Bayes	Text Blob classification model used for text classification.
Jolin Shaynn-Ly Kwan et.al. [20], 2021,	Data extracted from Twitter API. Preprocessing is done using standard procedures like stemming, lemmatizing and tokenizing.	LDA	Perplexity statistical measures.
Koyel Chakraborty et.al. [21], 2020	Senti WorldNet was used for assigning the sentiment score after the traditional cleaning process	AFINN	Valence Aware Dictionary and sentiment reasoner tool were used to analyze the tweets.

Table. 3: Modeling techniques employed in the literature

From Table. 3, experts have given the various contributions during COVID-19, which focused on sentiment behavior through the social media platform (see Fig. 5).



Sources	Lexicon	Machine Learning	NLP and Hybrid	Deep Learning
	13	6	5	4

Figure. 5: Sentiment analysis approach during COVID 19 [Table 2]

5. Research motivation:

Researchers and academics are driven to their respective fields for various scientific reasons. When it comes to sentiment analysis related to infectious diseases, researchers' interest and motivation can be categorized into two main classes: disease mitigation and data analysis.

5.1. Disease mitigation:

Many researchers are motivated by the importance of addressing infectious diseases and finding ways to mitigate their impact. Their focus lies in understanding public sentiment towards diseases, outbreaks, and health interventions. By analyzing sentiments expressed by individuals, communities, or even entire populations, researchers aim to gain insights into public perceptions, concerns, and behaviors related to infectious diseases. This information holds significant value in the development of impactful communication strategies, public health campaigns, and interventions aimed at managing disease spread. By extension, the adoption of technologies like data organization, data mining, and other artificial intelligence (AI) tools can enhance the processes of knowledge creation, storage, distribution, and oversight. This is analogous to a data storage environment where data mining techniques can uncover previously unnoticed data patterns, facilitating the generation of novel insights and information.

5.2. Data analysis:

Another driving force for researchers in sentiment analysis is the fascination with the potential benefits that can be derived from analyzing large volumes of data. Sentiment analysis provides a means to extract valuable information from social media platforms, online forums, news articles, and other sources of data. Researchers explore various techniques, algorithms, and models to analyze and interpret sentiments expressed in these data sources. By understanding public sentiments, researchers can identify patterns, trends, and emerging issues related to infectious diseases. This knowledge can contribute to evidence-based decision-making, policy development, and better understanding of public health dynamics.

These two categories, disease mitigation and data analysis, encompass the motivations and concerns of researchers in the field of sentiment analysis related to infectious diseases. Researchers strive to contribute to the broader understanding of public sentiment, public health interventions, and the effective utilization of data for disease control and prevention efforts.

5.3. Critical difficulties in decision-production during the Coronavirus - 19 pandemic:

COVID-19 has been universally acknowledged as the most disruptive and transformative event in recent memory, particularly from the perspective of corporate executives and managers. Decision-makers across all levels of management, spanning from top-tier corporate leaders to those responsible for operational aspects within the healthcare system, consider COVID-19 as the ultimate litmus test. It unquestionably represents the most formidable challenge in evaluating their decision-making prowess. Confronted with the unparalleled circumstances of the COVID-19 pandemic, decision-makers are compelled to act swiftly. They must grapple with comprehending a catastrophe previously unencountered, and navigate the critical decisions necessary to effectively manage and control the pandemic. These decision-makers collectively face formidable obstacles.

5.4. Motivation related to prevention of disease:

The world today faces new and challenging situations like epidemics and pandemics, such as COVID-19 and Ebola, which have a significant impact on the population and healthcare systems, leading to casualties and widespread panic. Traditional methods of dealing with these infections often fall short in effectively addressing the challenges they present. However, the use of smart and fast communication channels, particularly social media, has emerged as a crucial tool during disease outbreaks. Although COVID-19 is the ultimate test of managerial and leadership skills, one of the largest challenges for leaders and managers is poor information, which may be insufficient, inaccurate, uncertain, untrustworthy, vague, or only partially true. Due to the complexity of the virus and the pace of the epidemic, there is a severe paucity of data. On the other hand, decision-makers also have access to an abundance of false information that necessitates filtering and judgment.

Research efforts dedicated to sentiment analysis and opinion mining in the context of mitigating diseases, outbreaks, and infectious diseases have highlighted four key aspects where sentiment analysis has proven its significance:

1. Monitoring:

Sentiment analysis allows for tracking human activities and monitoring the spread of infectious diseases in different geographical locations. This helps in identifying hotspots, understanding public concerns and perceptions, and avoiding panic and misinformation.

2. Discovery:

The literature emphasizes two main aspects of discovery: rapid disease discovery and early disease detection. Sentiment analysis can aid in quickly identifying and monitoring disease outbreaks, as well as detecting early warning signs, enabling timely interventions and preventive measures.

3. News Sharing:

Social media platforms serve as effective channels for sharing news and information about diseases and outbreaks. Sentiment analysis plays a role in assessing public sentiments and reactions towards such news, facilitating the dissemination of accurate information and combating the spread of misinformation during health crises. It also enables the sharing of information about other emergencies and crises through social media platforms.

4. Policy and Strategies:

Sentiment analysis can be leveraged by governments and authorities to gain insights into public opinions and sentiments, enabling them to effectively control pandemics and manage epidemic outbreaks. By quickly analyzing sentiments expressed on social media, policymakers can issue timely health advisories, promote social distancing measures, and make informed decisions to address emergency situations.

Overall, sentiment analysis and opinion mining have demonstrated their relevance and importance in mitigating the impact of diseases, outbreaks, and infectious diseases. These tools and insights play a crucial role in the areas of monitoring, discovery, news dissemination, and policymaking, offering valuable support in the containment of pandemic spread and the effective management of epidemic scenarios. Given the novelty of COVID-19, decision-makers face a multitude of uncertainties. For instance, the reliability of information flows remains uncertain, human behavior proves unpredictable and unconventional, financial markets display irrational reactions, the economy exhibits extreme volatility, there is a dearth of data on measuring the impact of lockdowns, and outbreak patterns remain unknown. This unprecedented level of uncertainty makes it exceptionally challenging to make decisions within a fast-paced, high-impact environment where knowledge gaps exist, and clear-cut solutions are not readily apparent.

6. Proposed method:

The aim of this research paper is to introduce a two-stage approach to dimensionality reduction (DR) that is highly effective in the classification of textual content. The initial stage involves feature selection on the original feature space, resulting in a more compact feature set. During this step, features are ranked using the chi-square method based on their performance in the original space, and the highest-ranking features are chosen for the subsequent phase. In the second stage, feature extraction is carried out on the reduced feature set from the previous step. Principal Component Analysis (PCA) is employed to create a fresh feature space with significantly fewer dimensions. The performance of various learning algorithms is then assessed using this newly generated feature space.

Algorithm:

An algorithm for text classification that involves feature selection using chi-square in the first step and feature extraction using PCA in the second step:

Input:

- Training dataset (text documents with corresponding class labels)

- Number of desired features after feature selection (k)

Output:

- Predicted class labels for the test dataset

Algorithm: Text Classification with Feature Selection using Chi-Square and Feature Extraction using PCA

Step 1: Feature Selection using Chi-Square

1.1: Preprocess the training dataset (tokenization, stemming, etc.) to obtain a collection of text documents.

1.2: Calculate the chi-square value for each term (feature) in the training dataset, comparing its frequency in each class.

1.3: Rank the features based on their chi-square scores in descending order.

1.4: Select the top-k (k=50%) features with the highest chi-square scores.

Step 2: Feature Extraction using PCA

2.1: Preprocess the training dataset again, including the selected top-k features only.

2.2: Construct a term-document matrix, where each entry represents the frequency of a feature in a document.

2.3: Perform PCA on the term-document matrix to reduce its dimensionality.

2.4: Retain the principal components that capture a significant amount of variance (e.g., 95%).

2.5: Transform the training dataset using the retained principal components to obtain the reduced feature space.

Step 3: Training and Classification

3.1: Train a text classification model (e.g., Naive Bayes, Support Vector Machine, Logistic Regression, Artificial Neural Network, etc.) using the reduced feature space and the corresponding class labels.

3.2: Apply 10-fold cross-validation technique on the training dataset to evaluate model performance.

3.3: Tune hyperparameters of the classification model, if necessary.

3.4: Predict the class labels for the dataset using the trained classification model.

3.5: Output the predicted class labels for the dataset.

6.1. End of algorithm:

The algorithm presented is a comprehensive approach for text classification, aimed at efficiently processing and analyzing text data to accurately assign class labels. The process begins with feature selection using the Chi-Square statistical test, a powerful technique to identify the most informative features (terms) in the text data. By calculating the Chi-Square value for each term and comparing its frequency in different classes, the algorithm effectively determines the features that are most discriminative for classification.

Subsequently, the algorithm proceeds with feature extraction using Principal Component Analysis (PCA), which aids in reducing the dimensionality of the dataset while preserving its essential information. This step is vital for handling high-dimensional text data efficiently and preventing overfitting, as it retains the principal components that explain the majority of the dataset's variance. Consequently, the reduced feature space obtained from PCA significantly enhances the efficiency and performance of subsequent classification models.

In the final stage, the algorithm applies various machine learning models, such as Naive Bayes, Support Vector Machines, Logistic Regression, or Artificial Neural Networks, to train the text classification model. The model is built using the reduced feature space obtained from the previous steps and is evaluated using a 10-fold cross-validation technique to ensure robustness and avoid bias in the evaluation process. Moreover, hyperparameter tuning is carried out to optimize the model's performance, leading to more accurate predictions.

Overall, this text classification algorithm represents a powerful and systematic approach that efficiently processes raw text data, identifies relevant features using Chi-Square, reduces dimensionality with PCA, and leverages various machine learning models to achieve accurate and reliable text classification results. Its potential applications span across numerous fields, including sentiment analysis, document categorization, and spam detection, making it an indispensable tool for handling and extracting insights from textual information.

7. Discussion:

This article focuses on the analysis of sentiment and behavioral significance related to COVID-19. It extensively examines various aspects such as the dataset used, data sources, data cleaning methods, and other important factors that contribute to the research outcomes. The primary focus of many articles analyzed in this study is the infection ratio, death ratio, and spatial significance of infection and death rates. While some papers may explore Twitter trends during the spread or peak of the pandemic, this article places greater emphasis on factors and commonly used analysis algorithms.

The dataset utilized in this research is sourced from internationally recognized and reputable journals. However, in the current low-case scenario, Twitter activity related to COVID-19 is relatively quiet, with only official handles reporting daily cases. Conducting sentiment analysis on the current behavior becomes challenging. Nevertheless, comparative studies comparing the previous condition with the present scenario should be conducted to gain insights.

The study highlights the importance of improved user interfaces and advanced database administration for data archiving, tracking, and exploration in new dimensions. By incorporating different categories, groupings, and additional data analytics, the research can be further enhanced. The inclusion of objective assessments alongside emotional analysis would allow for comparative analysis and validation of the present findings. Future research could explore the adaptation of the code to accommodate the potential capabilities of tensor-flow, a machine learning framework, in order to improve the analysis. Executives, healthcare administrators, and experts are tasked with making critical decisions in situations of significant ambiguity, often facing substantial risks and severe consequences if those decisions prove to be poor. It is essential for decision-makers to assess these risks and take necessary measures to mitigate them. The current epidemic serves as a prime example of the complexity of decision-making amidst extreme ambiguity, especially when the potential outcomes in terms of fatalities and economic losses are irreversible. The characteristics of the COVID-19 pandemic demand swift judgments. Decision-makers must act promptly to ensure the right choices are made, as any delay could lead to loss of life and financial damage. To identify and evaluate tipping points and triggers for subsequent actions, decision-makers need to remain vigilant. However, making rapid decisions becomes exceptionally challenging when these individuals face intense pressure, significant threats, and profound uncertainty.

The inspiration for this work stems from the widespread impact of the COVID-19 pandemic. COVID-19 remains a highly uncertain and rapidly evolving infectious disease, making it challenging to obtain updated and accurate information. It is crucial to gather precise data when the pandemic eventually subsides. This research specifically focuses on the analysis of COVID-19 data using machine learning and deep learning techniques, as the pandemic has had a profound impact on the world. The review covers the period from 2019 to 2021, during which the disease reached its peak multiple times, causing significant changes in lifestyle worldwide. The psychological impact of the pandemic is still being analyzed, including its effects on people's lifestyles, healthcare systems, and the well-being of patients and frontline workers. Social media platforms play a crucial role in understanding these impacts.

8. Conclusion:

In conclusion, the article underscores the significance of sentiment analysis and behavioral insights in the context of COVID-19. It acknowledges the limitations in current Twitter activity but encourages comparative studies and suggests avenues for further research, including improvements in user interfaces, database administration, and expanding the analytical approaches employed. Although the current situation may show a decline in COVID-19 severity due to mass vaccination and increased awareness, it is essential to understand the challenges faced during previous waves of the pandemic. In this way, one of DSS's research areas becomes the creation of a set of conceptual underpinnings for future application and growth, an individual for each quadrant of the knowledge spiral. As an example, cognitive mapping might serve as a fruitful basis for the tacit to explicit knowledge conversion when used as a source of research to identify and examine the decision maker's mental representations of a certain decision-making environment. By addressing the psychological aspects and leveraging data analysis, we can empower ourselves in the face of pandemics. Scientists from various fields are working together to minimize the effects of COVID-19, and data analysis should be conducted with high accuracy to drive advancements in this regard. Additionally, studies should explore how our respective regions can contribute as valuable resources in the future. Considering the perspectives of computer science, integrating various technologies such as artificial intelligence (AI), machine learning (ML), and other analytical techniques can make a significant impact. We all hope that advancements in science and technology will prevent the recurrence of diseases like COVID-19, and it is crucial to work collectively towards that goal. The current study's particular emphasis is on the COVID-19 pandemic timeframe. Conducting a comparative analysis of the predictability of market panic across several time regimes would be fascinating and crucial. In the future, it would be possible to discriminate between the results from the Pre COVID-19, COVID-19, and Post COVID-19 time periods. Explainable artificial intelligence is effective in efficiently extracting the phase-by-phase relevance of the relevant features.

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