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Classification of supervised deep learning models for COVID-19 tweets sentiment analysis

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Abstract

Social media provided a successful management of human societies in light of global crises. Social media platforms have been considered the central authority in guiding society, receiving information and conducting business in many countries during the COVID-19 pandemic period in March 2020. The social platform has seen an increase in use of 45% for public platforms and 35% for the use of messages. This study suggests An AI-based model for predicting the likelihood of infection with COVID-19 through sentiment analysis and early detection using a Natural Language Processing library with deep learning techniques CNN. The model performed improved the distinction between patients who are 'positive' and patients who are 'natural' and unaffected are 'negative'. The performance of the model was tested using publicly available databases on Twitter for the period from March 16, 2020 to April 14, 2020.The achieved accuracy percentage was (~9%9.8)) and based on the four measures Accuracy, Recall, Precision and F1-score.

Keywords: Sentiment Classification; Deep Learning; Convolutional Neural Networks; COVID-19; Natural language processing

1. Introduction

Deep learning models, specifically Convolutional Neural Networks (CNNs), have become effective tools for sentiment analysis tasks in recent years [1]. CNNs are particularly adept at learning spatial hierarchies of features, making them well-suited for processing sequential data such as text [2]. By combining CNN architectures with NLP methodologies, researchers can create robust sentiment classification models that accurately categorise COVID-19 tweets into positive, negative, or neutral sentiment classes [3]. This study aims to investigate the use of NLP and CNN techniques in sentiment analysis of COVID-19-related tweets on Twitter [4]. By examining sentiment patterns over time, geographic regions, and topical themes, we aim to uncover nuanced insights into public attitudes, emotions, and perceptions surrounding the pandemic [4].

The results of this study have the capacity to provide valuable insights for public health strategies, crisis communication initiatives, and social policy interventions that try to tackle the complex issues presented by the COVID-19 pandemic [8].

The Coronavirus (COVID-19) outbreak has not only emerged as a worldwide health disaster but also as a substantial social and psychological phenomenon, impacting people's behaviours, emotions, and perceptions on a global scale. Twitter and other social media platforms have become influential avenues for individuals to promptly share their ideas, concerns, and responses to the pandemic in the digital era [9].

Sentiment analysis, a subfield of natural language processing (NLP), provides a valuable method for comprehending and examining the emotions conveyed in COVID-19-related messages on Twitter [9]. Researchers can utilise NLP approaches to analyse large volumes of text data and gain valuable insights. This allows them to identify patterns,

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trends, and changes in public sentiment towards the virus, government actions, healthcare measures, and social effects [10]. The subsequent sections of this study provide a detailed examination of the methodology, dataset, experimental setup, and results of our sentiment analysis. We emphasise the importance and consequences of utilizing natural language processing (NLP) and convolutional neural network (CNN) approaches to comprehend the changing public sentiment during the Coronavirus pandemic [11].

This analysis aims to elucidate the predominant emotion against COVID-19 on Twitter, offering significant insights for public health authorities, politicians, and researchers [14]. Analysing the changes in people's emotions can provide valuable insights for implementing specific actions, developing effective crisis communication plans, and implementing public health measures to address the social and psychological consequences of the pandemic [15].

The aim of the current study is to reach our findings as a contribution to the first understanding of analyzing individuals' feelings and anxiety during the Covid-19 crisis in order to develop a healthcare system that can effectively deal with human behavior and provide optimal guidance to society through social media platforms. Ensuring the safety of citizens by disseminating accurate information related to the pandemic, linking them with health authorities, and providing support and health updates.

2. Methodology

There are basic steps to be relied upon within the methodology of studying the introduction in this research and:

- Collect the data set to train and test the deep learning model.
- Preprocessing the dataset for post processing.
- Convert text data to vector form using NLP.
- Divide the data set into training and test groups.

2.1. NLP Techniques

Natural Language Processing (NLP) is type of function can be defined as a group of computational techniques that are characterized by their theoretical nature in automatic analysis and representation of human languages. NLP research has evolved from the age of punch cards and batch processing (with a sentence parsing time of about 7 minutes) to the age of Google and other platforms with millions of pages (which can be processed in less than a second).

The idea of this technique was created in the 1950s, and initial research in NLP focused on limited tasks such as machine translation, information extraction/retrieval, text summarization, answering questions, topic analysis, and modeling [16].

The majority of previous NLP implementations were hand-coded rule-based systems that were only able to perform some tasks related to natural language processing. The challenge came when these systems had to be expanded to account for the endless flow of exceptions or ever-increasing volumes of text and audio data.

Provides a statistical NLP, which automatically extracts, categorizes, and labels text and audio input items before each possible interpretation of these items is given a statistical probability. Convolutional Neural Networks (CNNs) and others are combined to create Natural Language Processing (NLP) systems that "learn" as they work and extract more precise meaning from massive amounts of unstructured text. Such as computer algorithms, machine and deep learning models as well as statistical NLP techniques and audio datasets that are not categorized or ordered. Natural language processing is the driving force behind machine intelligence in many modern real-world applications. Here are a few examples:

Spam detection, Machine translation, Virtual agents and chatbots, Social media sentiment analysis and Text summarization.

Most of the research at the time focused on syntax, due to the necessity of grammatical processing at that time and partly through implicit or explicit support for syntax-based processing despite the presence of semantic problems and NLP needs from the beginning [17].

More generally, NLP targets computer programs that translate text from one language to another, respond to spoken commands, and summarize large amounts of text quickly - even in real time. There are many examples now using this, such as voice-operated GPS systems, digital assistants, speech-to-text dictation software, chatbots for customer service, and other consumer conveniences. In business organizations, NLP provides solutions that help simplify critical business processes and increase employee productivity [17].

2.1.1. NLP tasks

Natural language generation is the process of converting structured data into human language; it is frequently referred to as the opposite of voice recognition or speech-to-text. Figure 1 shows Popular NLP Tasks

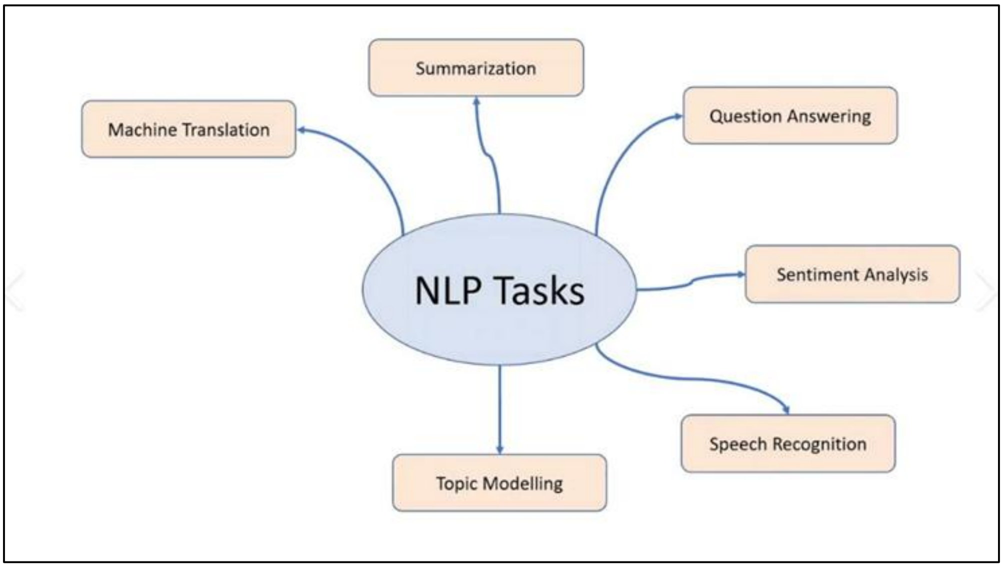

Figure 1 Popular NLP Tasks

2.2. Proposed System

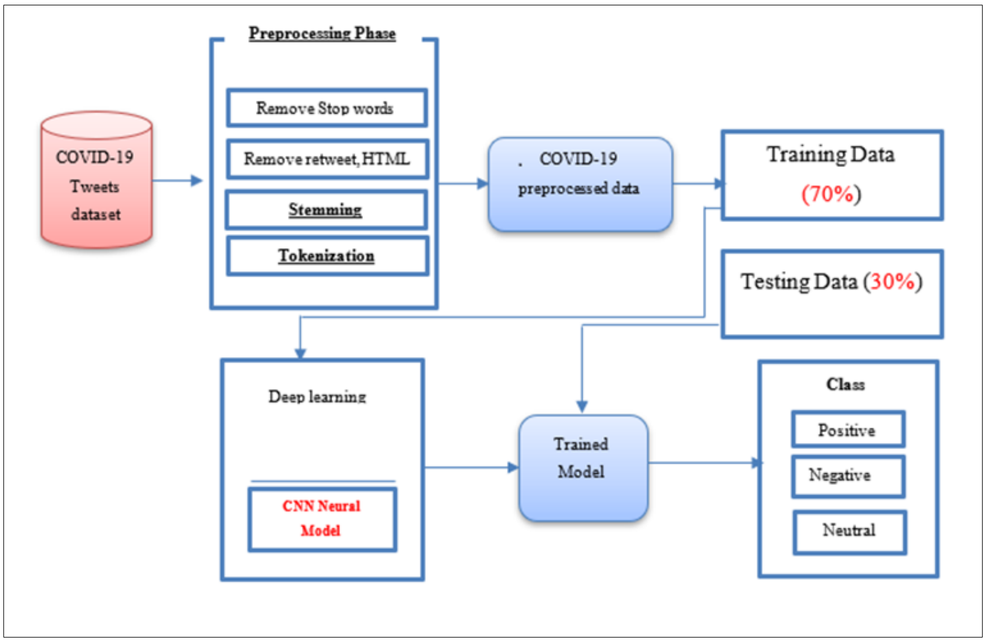

Figure 2 The proposed system of deep learning

The system proposed in this study consists of a set of steps for analyzing messages during the Covid-19 epidemic. Figure 2 represents the proposed flow chart for the system architecture. The dataset represents Twitter COVID-19. In order to initialize the data and facilitate the work of the advanced stages of the proposed system, texts are processed in the third stage and refers to the cleaning and preparation of tweets data for modeling. This stage includes: Remove all barriers, links and numbers, Remove Stopwords (common words like "the", "a" etc.), Remove Retweets, HTML, Stemming, Tokenization. Then the coding stage begins (the third stage) The words are encoded and routed. Converting tweet words into numbers. In the fourth stage, the data is divided into two groups: training and testing. Extracting the model and training the neural network is the last stage of the proposed system.

2.3. Data Set Features and Description

The dataset used in this study can be found on kaggle, a machine/deep learning database. There are 129,570 samples distributed over two data sets. The training data set includes 118,174 entries, accounting for 70% of the total data. 12386 for testing at 30%. Table 1 shows a sample of the data set

Table 1 Dataset sample and Features Description

London	16-03-2020	@MeNyrbie @phil_Gahrisitv https://t.c..	Neutral
UK	16-03-2020	advice Talk to your neighbours family to ex..	Positive
Vagabonds	16-03-2020	Coronavirus Australia: Woolworths to give e..	Positive
nan	16-03-2020	PLEASE, don't panic,THERE WILL ENOUGH F..	Positive
nan	16-03-2020	Not because I'm paranoid, but because my fo...	Negative
AT:36.319708,-82.363649	16-03-2020	As news of the regionAs first confirmed cov…	Positive
35.926541,-78.753267	16-03-2020	Cashier at grocery store was sharing his in…	Positive

2.4. Preprocess Step

Numerous symbols (including !, #, @, and others), numbers, punctuation, and stop words are permitted in tweets. Stop words are described as words that lack emotion. like that, he, she, and he. Sentiment analysis is not appropriate for this set of data. So that it could be processed further, we cleaned the data by eliminating punctuation, numbers, and symbols, and changing all of the characters to lowercase. The stop words were then taken out of the list of tokens after dividing the tweet into tokens. The basic shapes of each tweet after cleaning and pre-processing are stored in a list called vocabulary. Table (2) provides an illustration of the reprocessing results.'

Table 2 The Pre-processing of stop words and special characters

Tweet 1	#Delicious #Beef #Cheese #Burger @McDonald Testing CheeseBurger and Hamburger
After Pre-processing	[delicious ,beef ,cheese ,burger , mcdonald, taste ,cheeseburger ,hamburger]
Tweet 2	#Late Service @McDonald Delicious Hamburger but Slow service
After Pre-processing	[late, service , mcdonald ,delicious, hamburger , slow]
Vocabbulary	[delicious ,beef ,cheese ,burger , mcdonald, taste ,cheeseburger ,hamburger,late, service, slow]

The text cleaning process was carried out in four stages shown in figure (3) and based on the NLTK library of NLP for Natural Language Processing. The NLTK (Natural Language Toolkit) library provides a set of libraries and software for statistical language processing. NLTK is one of the most powerful NLP libraries, having packages that make machines understand and respond to human languages with appropriate responses.

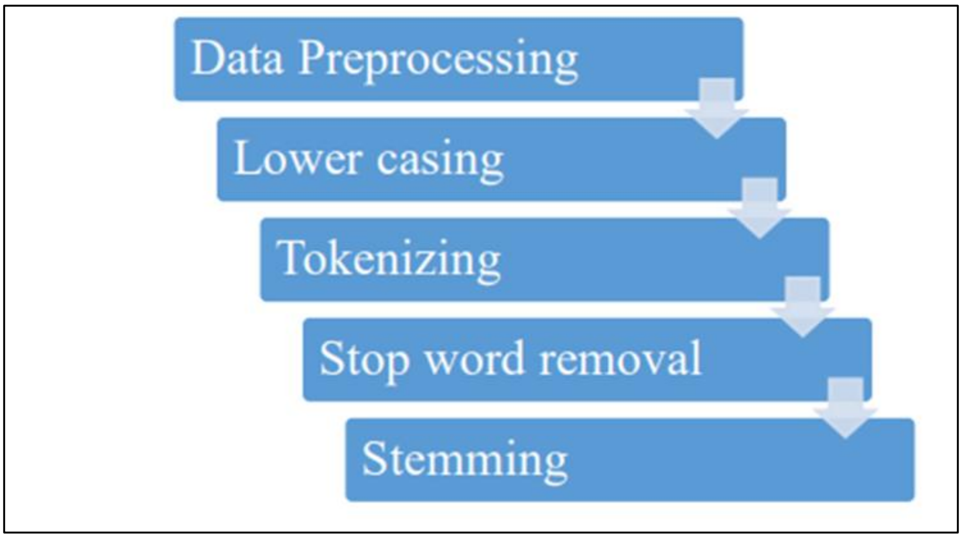

Figure 3 The steps in data pre-processing

2.5. Evaluation Metrics

The last phase of this work is the three-evaluation metrics that have been used for experimental results.

2.5.1. Accuracy measure

Classification when we use the term accuracy, we typically imply accuracy. The number of correct predictions divided by the total number of input samples is the ratio. It is mandatory to calculate the confusion matrix which include True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN).

Accuracy = (TP+TB) / (TP+TN+FN+FP) .... (1)

2.5.2. Recall

It is calculated by dividing the number of accurate positive findings by the total number of relevant samples (all samples that should have been identified as positive).

$$recall = \frac{TP}{TP + FN} \dots (2)$$

2.5.3. Precision

It is the number of correct positive outcomes divided by the classifier's expected number of positive findings.

$$precsion = \frac{TP}{TP + FP} \dots (3)$$

2.5.4. F1-score

The Harmonic Mean of accuracy and recall is the F1 Score. F1 Score has a range of [0, 1]. It informs you how exact and robust your classifier is (how many occasions it properly classifies). High precision but low

recall offers an extremely accurate result, but it also misses a huge number of occurrences that are difficult to classify. The higher the F1 Score, the better our model's performance.

$$F1 - Score = \frac{2 * precsion}{precsion + recall} \dots (4)$$

Where,
TP : True Positive is the number of times the attack traffic was correctly classified.
FN : False Negative is the number of times attack packets was classified as normal packets.

FP : False Positive is the number of times the normal packets was classified as attack packets. From the confusion matrix, The following performance measures can be identified: Accuracy

3. Results and discussion

In this section, we present the results of sentiment analysis for Twitter tweets using a hybrid approach combining Natural Language Processing (NLP) techniques and Convolutional Neural Networks (CNNs). The sentiment of tweets was classified into four categories: positive, negative, neutral.

We discuss the findings and implications of our analysis in understanding public sentiment dynamics amidst the Coronavirus (COVID-19) pandemic.

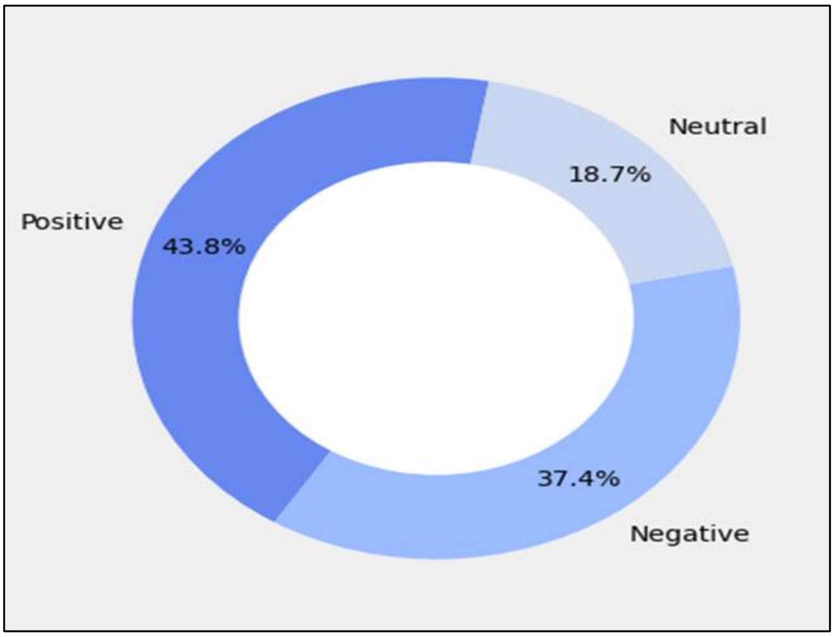

Figure 4 The structure of Twitter Covid-19 dataset

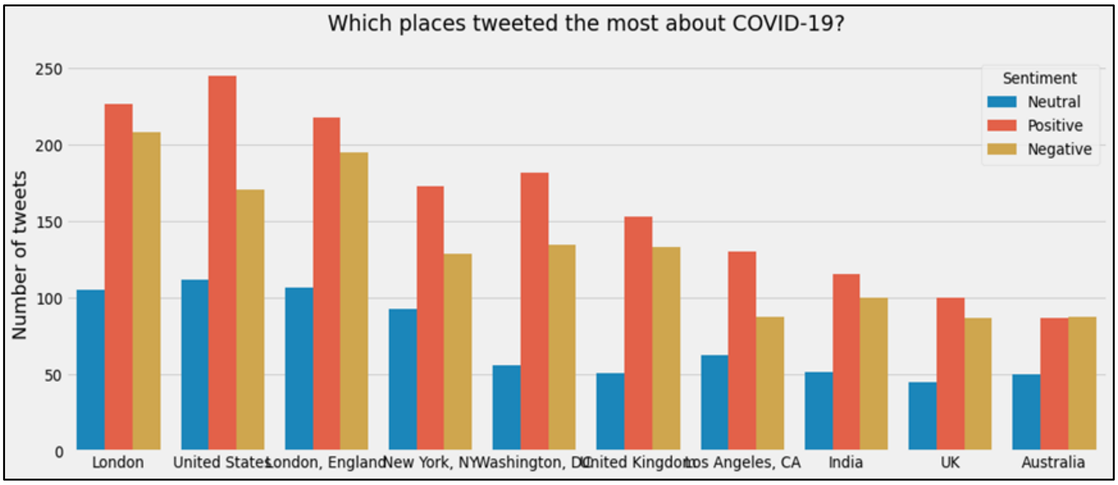

Figure 5 Twitter's COVID-19 sentiment classification by country geographic location

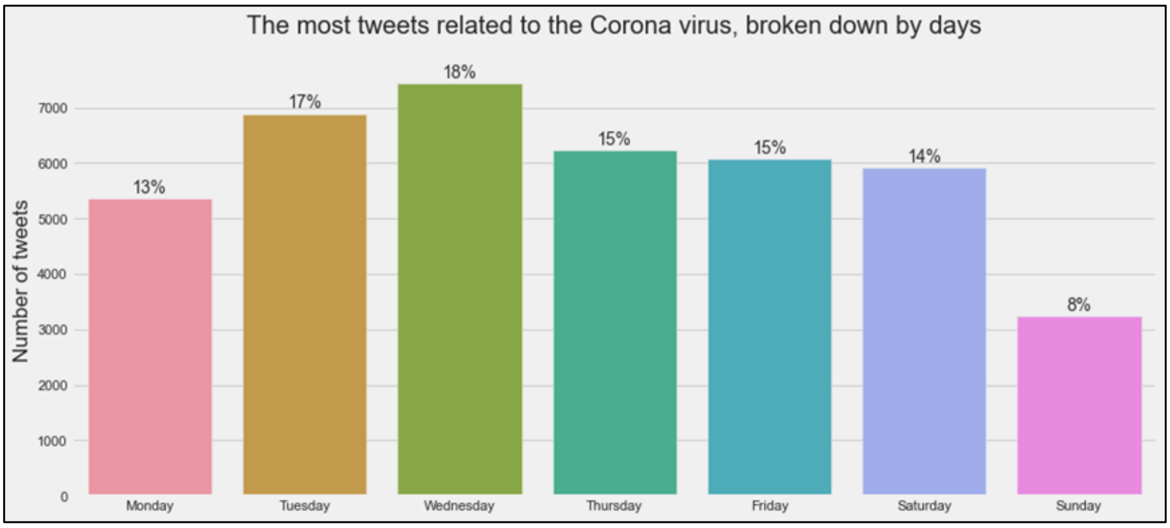

Figure 6 Twitter's COVID-19 sentiment classification by days of week

Figure (4) shows the percentage of Twitter analysis according to its status (normal, positive and negative). While the figure (5) and (6) shows the distribution of tweets classification according to geographical location and days.

3.1. Sentiment Classification Performance

The NLP and CNN-based sentiment analysis model achieved promising results in classifying the sentiment of COVID-19-related tweets. The model demonstrated high accuracy, precision, recall, and F1-score across all sentiment categories, indicating its robustness in capturing nuanced sentiment expressions in Twitter data.

The table (3) shows the behavior of deep learning algorithms on Twitter Covid-19 dataset by used the four scales (Accuracy, Precision,, Recall, F1 score) where the results showed the superiority of the CNN algorithm in performance efficiency and detection accuracy.

Figures (5,6) also show the behavior of the deep learning algorithms that have undergone training, where the training accuracy was compared with validation accuracy using random samples from the test samples.

Table 3 The performance of models on Twitter Covid-19 dataset

No,	Models name	Accuracy	Precision	Recall	F1 score:
2.	CONVOLUTIONAL Neural Networks (CNN)	99.80%	81.683%	87%	84%

The table (3) shows the behavior of deep learning algorithms on Twitter Covid-19 dataset by used the four scales (Accuracy, Precision,, Recall, F1 score) where the results showed the superiority of the CNN algorithm in performance efficiency and detection accuracy.

Figures (7,8) also show the behavior of the deep learning algorithms that have undergone training, where the training accuracy was compared with validation accuracy using random samples from the test samples.

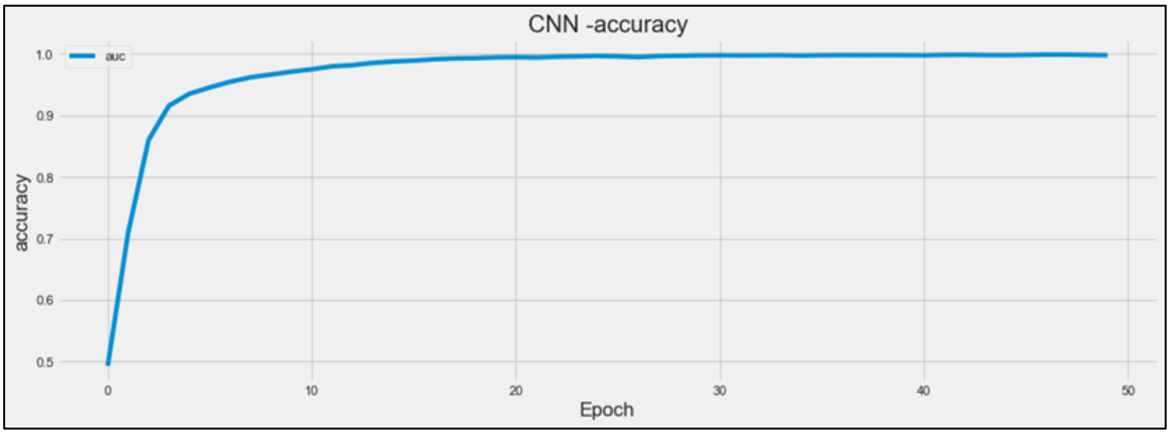

Figure 7 The behavior of the CNN algorithm in training phase

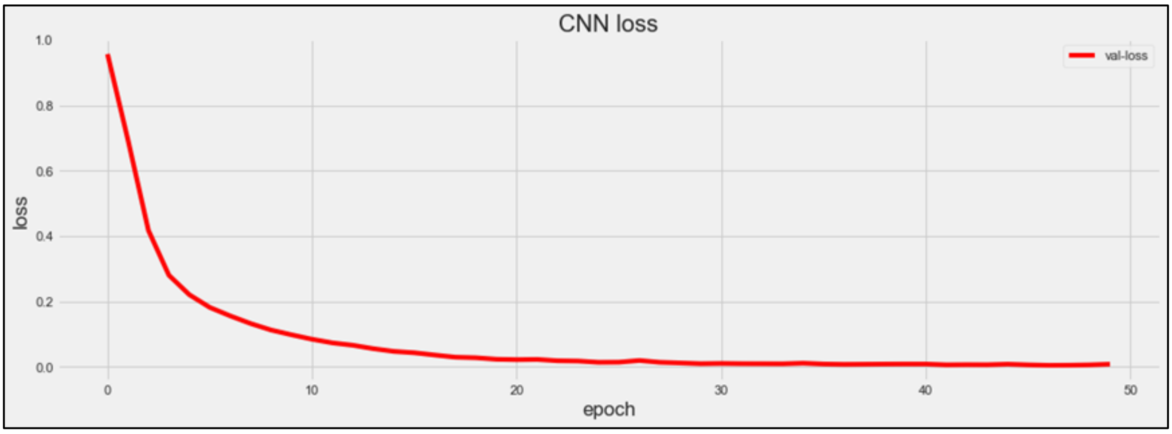

Figure 8 The CNN loss

3.2. Analysis of Sentiment Trends

Our analysis revealed significant fluctuations in sentiment trends over time, reflecting the evolving public perceptions and emotional responses towards the COVID-19 pandemic. We observed a surge in negative sentiment during peak infection periods and government policy announcements, indicating heightened anxiety and uncertainty among Twitter users. Conversely, positive sentiment spikes were observed following scientific breakthroughs, community solidarity initiatives, and successful vaccination campaigns.

4. Discussion and Implications

The results underscore the importance of leveraging NLP and CNN techniques for real-time monitoring and analysis of public sentiment on social media platforms like Twitter. By understanding the prevailing sentiment dynamics, policymakers, public health authorities, and crisis communicators can tailor their interventions and messaging strategies to address specific concerns, alleviate fears, and foster community resilience amidst the ongoing pandemic.

Furthermore, the insights gained from sentiment analysis can inform targeted interventions, public health campaigns, and mental health support services aimed at addressing the psychosocial impacts of the COVID-19 crisis. By harnessing the power of NLP and CNN technologies, we can gain deeper insights into the collective psyche of society and mobilize resources effectively to navigate through these unprecedented times.

4.1. Limitations and Future Directions

While our study provides valuable insights into sentiment trends on Twitter, it is not without limitations. The analysis is based on publicly available Twitter data, which may not fully represent the diverse perspectives and experiences of the population. Future research could explore alternative data sources, incorporate multimodal inputs (e.g., images, videos), and refine sentiment analysis models to enhance their accuracy and generalizability across different contexts and languages.

In conclusion, the integration of NLP and CNN methodologies offers a powerful approach for analyzing sentiment in Twitter tweets related to COVID-19. By harnessing these technologies, we can gain timely insights into public sentiment dynamics and inform evidence-based decision-making in crisis management and public health response efforts.

5. Conclusion

Since the outbreak of the COVID-19 epidemic on March 6, 2020, and the imposition of social restrictions on citizens all over the world, social media has played a primary role in managing the joints of life for citizens. Twitter alone saw a sharp 45% increase in curated events page use, and a 30% increase in its use of direct messages. In this study, we analyzed the psychological impact, sentiment analysis, and association on information related to the COVID-19 virus. Our proposed system was designed using deep learning techniques (CNN) and Natural Language Processing Library (NLP) and achieved accuracy (99.8%) for CNN algorithm and using the Twitter COVID-19 dataset.

We present our findings as a contribution to the early understanding of analyzing the sentiments and fears of individuals during the COVID-19 crisis to build a health system capable of managing human activity and optimally guiding society using social media platforms. Protecting citizens through receiving false information related to the epidemic, linking individuals to health authorities, and receiving health support and health bulletins.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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