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ORIGINAL RESEARCH

Omicron virus emotions understanding system based on deep learning architecture

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Abstract
Emotions understanding has acquired a significant interest in the last few years because it has introduced remarkable services in many aspects regarding public opinion mining and recognition in the field of marketing, seeking product reviews, reviews of movies, and healthcare issues based on sentiment understanding. This conducted research has utilized the issue of Omicron virus as a case study to implement a emotions analysis framework to explore the global attitude and sentiment toward Omicron variant as an expression of Positive feeling, Neutral, and Negative feeling. Because since December 2021. Omicron variant has gained obvious attention and wide discussions on social media platforms that revealed lots of fears and anxiety feeling, due to its rapid spreading and infection ability between humans that could exceed the Delta variant infection. Therefore, this paper proposes to develop a framework utilizes techniques of natural languages processing (NLP) in deep learning methods using neural network model of Bidirectional-Long-Short-Term-Memory (Bi-LSTM) and deep neural network (DNN) to achieve accurate results. This study utilizes textual data collected and pulled from the Twitter platform (users' tweets) for the time interval from 11-Dec.-2021 to 18-Dec.-2021. Consequently, the overall achieved accuracy for the developed model is 0.946%. The produced results from carrying out the proposed framework for sentiment understanding have recorded Negative sentiment at 42.3%, Positive sentiment at 35.8%, and Neutral sentiment at 21.9% of overall extracted tweets. The acquired accuracy using data of validation for the deployed model is 0.946%.

Keywords Deep learning · COVID-19 · LSTM · Omicron virus · Emotion analysis · Bi-LSTM · NLP

1 Introduction

In late November 2021, Omicron is one of the COVID-19 virus variants. It was diagnosed in South Africa and Botswana, this variant was swiftly categorized by the World Health Organization (WHO) as an issue of concern. The Omicron variant of the COVID-19 virus once again changed the course of the pandemic. In epidemiology, the available data regarding Omicron recommended that this kind of virus can significantly evade the immune system and is more infectious than the Delta form. Besides, the WHO classifies the risk associated with Omicron as very high. Besides, this new variant is scientifically known as B.1.1.529. 46 US states and over 90 other countries have both reported finding Omicron. Unlike in area of South Africa and region of Botswana, where limited instances of COVID19 were recorded at the time Omicron emerged, there was an increase in infections due to the Delta variant in the United States. By December 2021, around 70,000 people have been hospitalized in the U.S., and averages of 1,300 deaths per day are attributed to COVID-19. Nationwide, Omicron has developed into the dominant variant in less than 3 weeks and is now represented with 73% from samples for the week ending December 18, 2021 (Luo et al. 2021). On December 13, 2021, the UK health authority UKHSA revealed that an infected patient had passed away in England the Omicron variant of COVID-19. The day before, Prime Minister Boris Johnson launched a campaign to offer all adults in the UK a third dose of the COVID-19 vaccine before the end of the year. "Now we're

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facing an emergency," said Johnson. "There is a tidal wave of Omicron coming and I am afraid it is now clear that two doses of vaccine are simply not enough". To the press, the UK had recorded 10, 017 cases of Omicron. The actual case is likely to be significantly higher. On December 15, 2021, 78,610 people tested positive on COVID19 in the UK (Luo et al. 2021; Hoffmann et al. 2021; Lopez Torres 2021; Mostafavi et al. 2022). Given the experience in South Africa and Europe and now in the US, Omicron is likely to displace the dominant variant Delta in much of the world. China has also identified 11 cases infected with Omicron by December 15, 2021. There is considerable uncertainty regarding the transferability and severity of Omicron. Researchers at the University of Hong Kong found that Omicron infects and reproduces COVID-19 70 times faster than the Delta variant and the parent COVID-19 in the human bronchus, but the infection in the lungs is significantly lower than in the parent group COVID-19 (Luo et al. 2021). The latest study recommends that the Omicron variant could be further adept at infecting recovering people compared to the last circulating variants (Hoffmann et al. 2021). Therefore, the omicron variant forms a fast-evolving threat to public health and might weaken efforts of the global to fight and limit the COVID-19 pandemic. However, the susceptibility of the Omicron variant to antibody-mediated neutralization has yet to be analyzed. The antibodies are ineffective and likely to interfere with the protection provided by the antibodies induced following infection or vaccination with two doses of BNT162-2 (BNT) (Abdullah 2021; Pulliam et al. 2021). Most of the hospital admissions and deaths are unvaccinated. However, more and more so-called breakthrough infections are diagnosed in people completely obtained vaccine, and also have gotten a boost injection of vaccine. To present, the majority of these infections have not led to a significant clinical illness. Although vaccination does not prevent all infections, vaccination so far offers protection against serious illness, hospitalization, and death. The extent to which current vaccines protect against serious illnesses associated with the Omicron variant must be carefully monitored (Del Rio 2021). However, the information regarding the severity of illness that comes from Omicron infection, and whether can be tolerated for COVID-19 vaccines needs time to be carefully investigated.

On the other hand, Omicron variant has been a hot topic of discussion on social media platforms that implied different feelings of fear, sadness, and anticipation. Previous conducting research showed that social media is an excellent source that could benefit in realizing the public's behavior or sentiment toward a particular topic (Buntain et al. 2016; Wang and Zhuang 2017; Chatfield and Brajawidagda 2012; Earle et al. 2011). Twitter belongs to social networking sites that people from the entire world logged in for socializing and discussing different issues that touch their lives. Investigating glob sentiment on the Twitter platform can be applied in different aspects such as the development of sociality, economic advancement, and public awareness (Madhukar and Verma 2017; Kandhro et al. 2020). However, Omicron variant is one of those topics extensively discussed on the Twitter platform. Omicron strain has passed through multiple mutations, the matter that triggered the anxiety and concern of scientists. Besides, the emergency and threat that Omicron virus caused around the world could confuse or hesitant people from taking the vaccine or even make people suffer feelings of fear. That could harm their immune system and even may damage their lifestyle after protocols of awhile managing COVID-19. Thus, there is a need to analyze data from social media to get to know people's sentiments toward the Omicron virus, and how they think about it as an expression of positive feeling, Neutral, and Negative feeling. Also, to understand the public emotions toward this virus to figure out factors that could affect people's lives negatively. For example, the psychological factor could affect people's health and economic factor could impact people's make living. Therefore, this paper aims at conducting a sentiment analysis study for the data collected from Twitter concerning Omicron posts to analyze these data and predict public emotions toward the new variant of Omicron virus.

2 Related work

Sentiment analysis based on natural language processing (NLP) is the process of text mining to understand and estimate people's opinions toward a particular issue in the form of Positive, Negative, and Neutral sentiments. Sentiment analysis has acquired a significant interest in the last few years because it has introduced remarkable services in many aspects regarding public opinion mining and recognition in the field of marketing, seeking product reviews, reviews of movies, and healthcare issues based on sentiment understanding. This conducted research has utilized the issue of Omicron COVID-19 virus as a case study to implement a sentiment analysis framework to explore the global attitude and sentiment toward Omicron variant (Madhukar and Verma 2017; Gurav and Kotrappa 2020; Liu et al. 2020; Zucco et al. 2020). Many studies regarding COVID-19 virus sentiment analysis have been proposed lately (Garcia and Berton 2021; De Melo and Figueiredo 2021; Nemes and Kiss 2021; Basiri et al. 2021; Khan et al. 2020; Almotiri 2022; Avasthi et al. 2022; Mohamed et al. 2022). Yet at the time of conducting this research, there is a limited number of research papers that highlight the issue of investigating public sentiment toward Omicron variant. A study by Mahyoob et al. (2022) proposed a sentiment framework for Omicron variant utilizing software named "SentiStrength" which applied natural language processing (NLP) text preprocessing methods based on lexical sentiments expressions and a group of linguistic procedures. Their study performed data gathering from platform of Twitter for the time-frame from 3rd Dec. 2021 to 26th Dec. 2021. A research paper introduced by Wang et al. (2022) aimed at exploring the public's perception of Chines people against Omicron variant. They used data collected from Weibo for the time frame from 27 November 2021 to 30 March 2022, using LDA-based topic modeling and ontology of DLUT emotion. Likewise, a study suggested by Thakur and Han (2022) conducted an exploratory method on data collected from Twitter about Omicron to mine the public sentiment. The data was collected from May 5, 2022, to May 12, 2022, based on a research tool called "Social Bearing" for performing Twitter research. Hosgurmath et al. (2022) Undertook a sentiment analysis system for Omicron utilizing NLP techniques and the Bag of Word method. Though, up to date, there are inadequate numbers of studies that investigate the public sentiment in concern with Omicron variant using deep learning techniques. The contribution of this paper is listed as follows:

1. Developing a deep learning model to predict general public sentiment toward Omicron virus using data collected from Twitter platform posts.
2. Data collection was carried out by extracting tweets on the Omicron virus from platform of Twitter between 11 December 2021 and 18 December 2021.
3. Deploying an Omicron sentiment understanding model using (BI-LSTM) and deep neural network layers (DNNs) by which high performance has been achieved. That's besides the introduced model's ability to analyze and make sentiment predictions on big data.
4. A large-scale dataset of Twitter is used to train and validate the proposed model.
5. This paper introduces a study to analyze the general people's emotions from the issue of Omicron virus the variant of COVID-19 as an expression of Positive feeling, Neutral, and Negative feeling, to help health organizations and humanitarian organizations deal with issues that might have affection on people life from different aspects.

The rest of this paper is organized as follows Sect. 2 discusses the methodology including model construction and model prediction; Sect. 3 discusses the results, and Sect. 4 discusses the conclusion.

3 The methodology

This paper has undertaken a sentiment analysis system using deep learning techniques to realize in general human emotion from the issue of Omicron variant for countries from around the world depending on data posted on the Twitter platform (tweets data). This research has been undertaken using NLP procedures. The framework of the developed system is depicted in Fig. 1. This study includes developing a sentiment analysis model architecture via adopting NLP methods and Bi-LSTM network. The system execution has done in two stages: the model construction stage, and the model deployment stage. The first stage includes reading the training dataset to perform data cleaning and tokenization. Then, create and set the model design to follow that

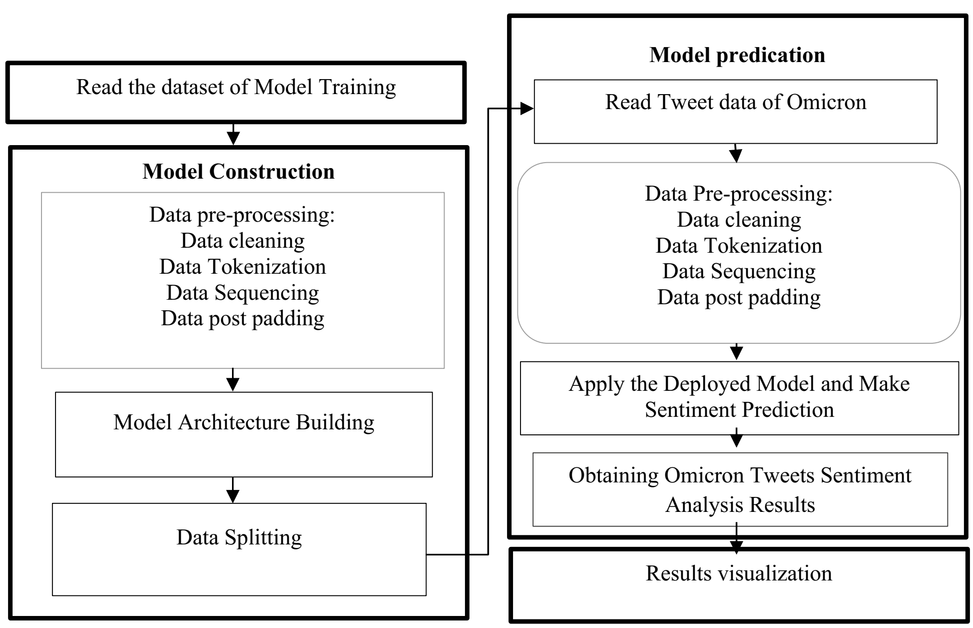


Fig. 1 The framework of the proposed system

completes the model training and validation to obtain the deployed model for sentiment analysis. The second stage is to utilize the deployed model to carry out sentiment prediction on the collected Omicron tweets data just after data cleaning and preprocessing. As a result, the model analyzes the tweets data and classifies them into three sentiment classes: "Negative, Neutral, and Positive". Finally, the gotten results from the analysis method are visualized.

3.1 Model construction

3.1.1 Preparing data for training

This work has utilized four datasets collected from Twitter for sentiment understanding to train the developed model. These datasets are made available to the public on the Kaggle repository. These datasets belong to different topics of sentiment analysis. It has been generally employed to perform model deployment in the field of sentiment analysis. The used datasets are founded in the form of a ".csv" file and named "tweet_dataset ", "apple-twitter-sentiment-texts", "Twitter-and-Reddit-sentimental-analysis-dataset", and "airline-sentiment" datasets. These datasets are concatenated together to be composed of 358,897 tweets after removing duplicates, "null", and "NAN" tweets and sentiments.

This step is followed by data pre-processing which prepares the dataset for the model to train on via removing URLs, emails, and non-alphabet characters, and removing all the punctuation signs and un-required characters. Then perform data tokenization and sequence padding by transforming the data into a list of lower words and then into a sequence of numbers to apply zero post padding based on the lengthiest sentence in the training dataset. The step after is splitting the dataset into training and testing.

3.1.2 Model architecture building

The next process in this stage is the proposed model architecture building for Omicron variant sentiment analysis. The developed model is built using a sequential model of Keras API tensorflow2 in python. The proposed model consists of an embedding layer of the Keras library for Python3. An embedding layer is responsible for representing each word in the sequence or text as a vector of words that has a size equal to the embedding dimension alongside considering encoding the words that have similar meanings with the same encoding value. Besides, the embedding layer works on mapping input data into the BI-LSTM network layer in the next step of model construction. It takes as input the total words as a max-features variable which is computed and is equal to 80,000, the embedding dimension is 64. The input shape for the embedding layer is equal to the computed max-length sentence in the training data which is in our study equal to 120.

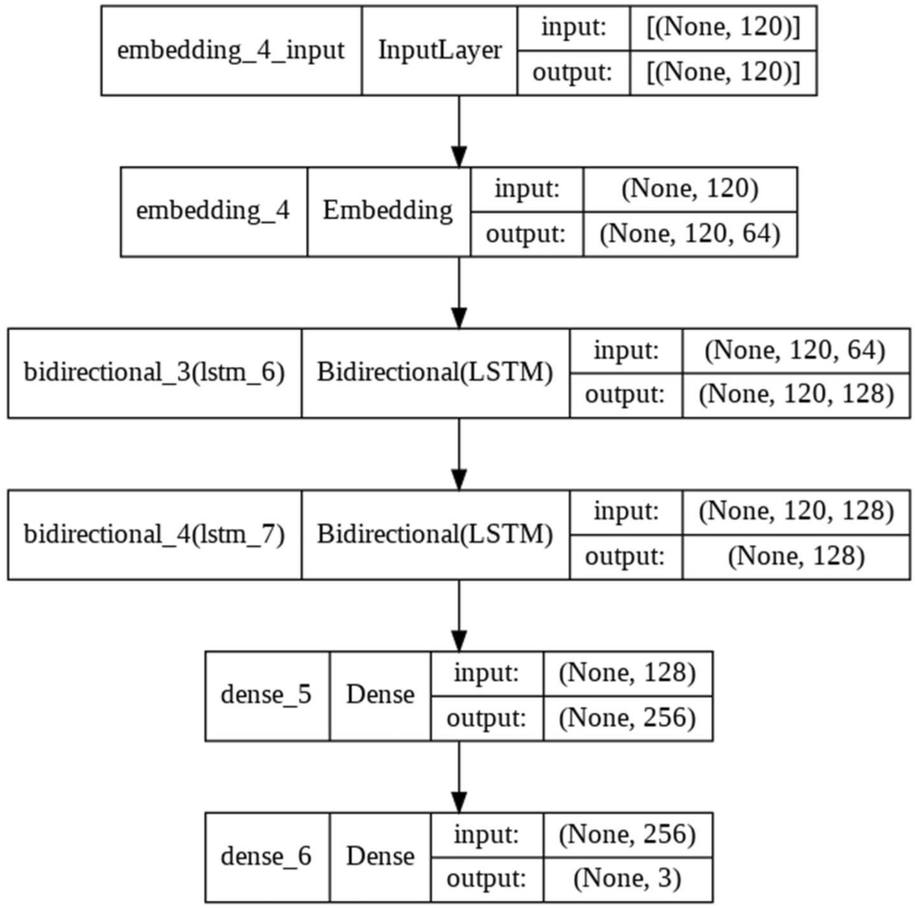
Next to the embedding layer, the proposed model has two BI-LSTM layers with a built-in dropout layer as a regularization technique to avoid or decrease overfitting problems. Since dropout considers one of the important hyper-parameters that can effectively advance the performance of the network training. This significance comes beside the number of neurons that have to be assigned to each layer of the BI-LSTM network to ensure the efficient work of the developed model. Thus, the number of neurons for the first and second BI-LSTM network layer is set with 64 neurons, while the assigned values for the dropout parameter are 0.6 and 0.9 for each sequentially. Two independent models of LSTM provide together information about the text-sequence in backward and forward direction at each time step in models of BI-LSTM, which process data in two different directions. This made accessing information at extended state is possible, and it has proven useful for solving word embedding and a number of other problems relating to processing the sequence, more information regards the BI-LSTM network can be reached within (Chandra and Krishna 2021a, b). In order to get accurate results for this study, a dense layer-based DNN network is proposed for this model with 256 neurons based on a "Relu" activation function. The last layer in this proposed model is a classification-dense layer with 3 categorical neurons and a "Softmax" activation function.

For the model compilation, the "Adam" optimizer is proposed due to its ability to make the network learns effectively and "Categorical-Crossentropy "is proposed as a loss function because of this multi-classification problem. The accuracy metric and loss error is used as a performance measure for training and validation operation during the model training process. The final important step in this model construction stage is model fitting and training, in which other hyper-parameters values are required to be assumed based on try-and-error till obtaining an accurate performance for the developed model. These hyper-parameters are epoch and batch-size parameters that have an essential role in model training and fitting. In this work, the proposed value for the epoch parameter is 8, and the proposed value for batch size is 64 experimentally. The model fitting operation is based on "Model Checkpoint", and Callbacks of Keras to monitor and save only the best model based on validation accuracy and Callback checkpoint from the previous epoch. Besides, the best model gotten from the training process is saved in the ".h5" file in order to be used in the prediction stage of this study. The architecture of the model has depicted in Fig. 2.

3.1.3 Bidirectional long short-term memory (Bi-LSTM)

The framework of the LSTM network is similar to that of a traditional RNN, but it calculates the hidden state in a

Fig. 2 The architecture of Omicron sentiment prediction model



different approach, which can alleviate the problem that RNNs can't handle far-reaching dependence. The exceptional skills of LSTM, on the other hand, are taught through the inherent advantages of its model structure, not through algorithms. The LSTM model is made up of a sequence of memory units that each includes three gates with various functions. The following are the values of the respective states of the LSTM unit of the tth word, using the text feature vector S as input and the t^{th} word as an example: the calculating formula is as follows: where dot multiplication is used and σ represents a sigmoid function (Long et al. 2019). The forget gate is represented by the letter f_t:

$$f_t = \sigma(W_f w_t + U_f h_{t-1} + b_f) \tag{1}$$

The input gate is as follows:

$$i_t = \sigma(W_i w_t + U_i h_{t-1} + b_i) \tag{2}$$

The candidate memory cell state at the current time step is denoted by $\widetilde{c}_t$, while the tangent hyperbolic function is denoted by tanh.

$$\widetilde{c}_t = \tanh(W_c w_t + U_i h_{t-1} + b_c) \tag{3}$$

The value of $\widetilde{c}_t$ in a memory cell represents the current time's state value: the value of f_t and i_t, which ranges from 0 to 1. Its computation $i_t \odot \widehat{C}$ indicates which new information from the candidate unit $\widetilde{c}_t$ is stored in c_t. $f_t \odot c_{t-1}$ is a calculation that shows which information is maintained and which is lost in prior memories c_{t-1}.

$$c_t = i_t i_t \odot \widehat{C} + f_t \odot c_{t-1} \tag{4}$$

The output gate is the o_t:

$$o_t = \sigma(W_o w_t + U_o h_{t-1} + b_o) \tag{5}$$

h_t is the state of the hidden layer at time t:

$$h_t = o_t \odot \tanh(c_t) \tag{6}$$

The long-short term memory of LSTM model simply considers the sequence's past knowledge, which is frequently insufficient. It would be very helpful for the sequence of tasks if you could access future information in the same way you could access prior information. A forward long-hort term memory layer and a backward long-short term memory layer make up the bidirectional LSTM. The following is the operating principle: the forward layer captures the sequence's previous information, while the backward layer captures the sequence's future information. The output layer for both layers is the same. The most notable feature of these structures is that the sequence context information is completely considered. Consider the following: at time t-1, the forward hidden unit's output is $\overrightarrow{h_{t-1}}$ 1, and the backward hidden unit's output is $\overleftarrow{h_{t+1}}$, and the input of time t is the word embedding w_t. Then, at time t, the outputs of the backward and hidden units are equal (Chandra and Krishna 2021a, b).

$$\overrightarrow{h_t} = L(w_t, \overrightarrow{h_{t-1}}, c_{t-1}) \tag{7}$$

$$\overleftarrow{h_t} = L(w_t, \overleftarrow{h_{t+1}}, c_{t+1}) \tag{8}$$

where L(.) signifies the LSTM hidden layer's hidden layer operation. The forward output vector is $\overrightarrow{h_t} \in R^{1xH}$, while the backward output vector is$\overleftarrow{h_t} \in R^{1xH}$. These two vectors should be merged to get the text feature (Long et al. 2019). On the other hand, BI-LSTM models handle data in two different directions, as opposed to models of Bi-RNN, which use only the past context state to predict the upcoming states. Two independent models of LSTM give together backward and forward information about the text- sequence at each time step. This made accessing information at extended state is possible, and it has proven useful for solving word embedding and a number of other problems relating to processing the sequence (Chandra and Krishna 2021a, b). This work suggested one layer of BI-LSTM having 64 units, identically as the embedding dimension, as shown in model architecture Fig. 2.

3.2 Model deployment and predicition

The deployment stage is the next stage of this study which is required to predict the sentiment toward Omicron variant. The data that we extracted from Twitter platform for the period from 11- December- 2021 till 18-December 2021 is fed as input to the deployed model from the first stage output. At first, this stage begins with uploading and reading collected data. Then, it commenced with data cleaning to remove duplicate and "NAN" data, and data preprocessing to remove URls, emails, non-alphabet characters, remove all the punctuation signs and all un-required characters similar to pre-processing operation utilized in the construction stage of this study. The number of extracted tweets data that are included in our study is 19982 tweets out of 20,032 tweets after removing duplicated tweets. Then applying data tokenization and sequence padding to transform the data into a list of lower words and then into a sequence of numbers to apply zero post padding based on the max-length parameter from the construction stage, using Tokenizer and sequencing from Keras API Tensorflow library. Tokenization, sequencing, and Padding are essential steps in NLP since it has the role to make the data ready for the deployed model to work on. The step after is using our developed model on the tokenized data to estimate the sentiment from each input tweet in the form of "positive, Negative, and Neutral".

4 Results and discussion

This paper developed a model that can predict sentiment about Omicron virus from Twitter posts as an expression of Positive feeling, Neutral, and Negative feeling, to examine and understand people's emotions from this recently emerged COVID-19 variant. Because of its high ability to transmit infection among people, the matter has raised the concern of WHO and health specialists in all countries. In addition, people around the world have their worries about Omicron virus and they express that through social media platforms like Twitter. This study has been implemented using the Python 3.7 programming language via utilizing NLP techniques and the Keras Tensorflow library. The code was executed on GPU of google Colab platform. The data that have been used for model training have been described in the methodology section, containing 358,897 tweets after cleaning. The training data was divided at random into 33% testing data and 67% training data. The data on the Omicron virus has been collected from the Twitter platform using the Python Twin tool library. The evaluation metrics that were utilized during the process of model training and fitting is the accuracy metric based on "ModelCheckpoint" of "Keras callbacks" to save the best model performance based on validation accuracy. As a result, the obtained accuracy after

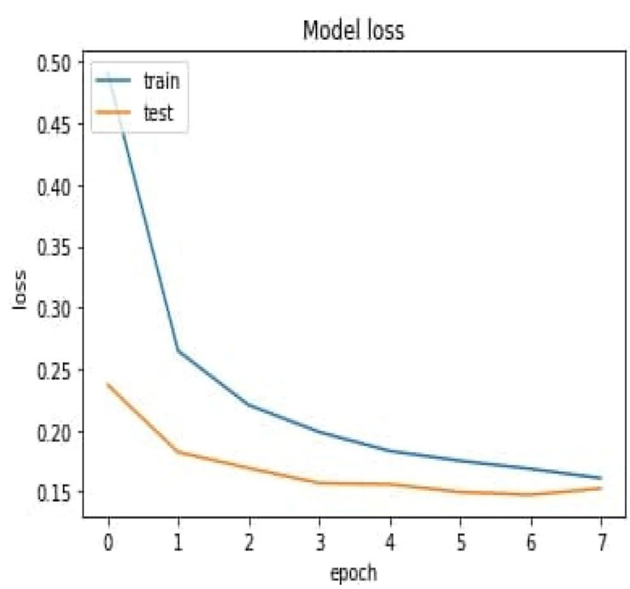


Fig. 3 The plot of loss error for each epoch through model training process

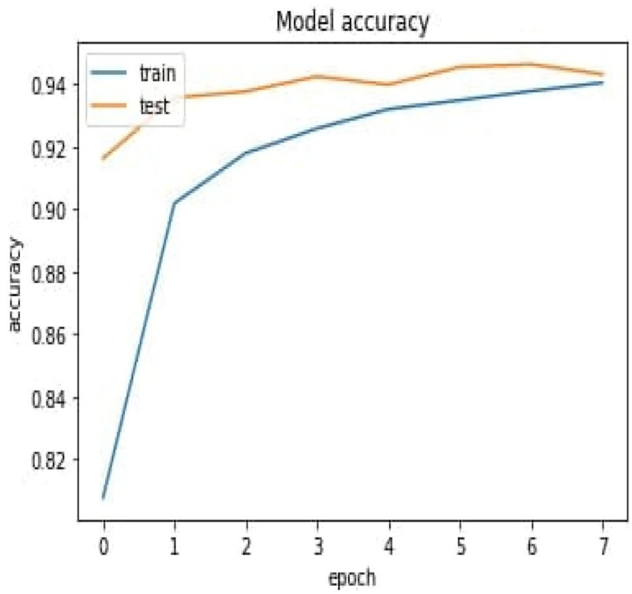


Fig. 4 The plot of accuracy metric for each epoch through model training process

Table 1 The achieved results based on Precision, Recall, and F1-score metrics for each sentiment category on test data

Category	Precision	Recall	F1-score
Neutral	0.952	0.933	0.943
Positive	0.925	0.920	0.922
Negative	0.952	0.970	0.961
Average	**0.943**	**0.946**	**0.942**
Average accuracy	**0.946**		

Bold values indicate the good performance of the proposed model

model training phase was 0.9403 for the training dataset and 0.9430 for the validation dataset. The model loss error and model accuracy plots for all epochs are illustrated in Figs. 3 to 4. Based on conducted experiments, and as shown in Fig. 4, the accuracy of model training and validation are increased with no of epoch till epoch equal to 8, but what has been noticed is that after epoch 8 the model may face an overfitting problem due to exaggerating training process. So, to make a trade-off between the model and data–of–training, the epoch as one of the essential hyper-parameters was assigned a value of 8.

Further evaluation is performed based on the test dataset by computing metrics of precision, recall, and F1-score for each category in addition to their average via using the "Sklearn" python library, the achieved outcomes for the calculated metrics are shown in Table 1. As appeared in Table 1, the Neutral and Negative sentiments have the highest Precision value, while the Recall metric value for the Negative sentiment category has gained 0.970 among the other two sentiments. On the other hand, F1-score has achieved a high value in the Negative sentiment category. The computed average of Precision, Recall, and F1-score metrics for each category (Neutral, Positive, Negative) are 0.943, 0.946, and 0.942 respectively. The overall average accuracy for all categorical sentiments is 0.946.

After model training and fitting within the construction stage, the trained model become equipped to provide a prediction. Therefore, the results that have been achieved from implementing our deployed sentiment model on Omicron Twitter dataset extracted for the time interval from 11- December- 2021 to 18-December-2021 are as follows:- 7093 tweets have Negative sentiment, 3667 tweets have Neutral sentiment, and 6009 tweets have a positive sentiment. Consequently, the overall sentiment is Negative followed by Positive and Neutral sentiments. What can be understood from these prediction results is that most people in their posts on Twitter have their worries and fear toward Omicron virus due to its rapid transmission and also since it is still under investigation by health specialists as well as there is no clear information about this type of COVID-19 variant yet. On the other hand, another group of people on Twitter shows positive emotion from Omicron virus represented in the possibility of tolerating and managing against this virus because of its mild symptoms in comparison with COVID-19 virus and Delta variant. Lastly, a small group of people within our collected Omicron Twitter dataset express Neutral sentiment from Omicron virus in their posts represented in posting news as it and waiting for formal information from health organizations about this variant as long as the issue of Omicron virus is under research. A flowchart shows the outcomes of Omicron sentiment prediction illustrated in Fig. 5.

Further visualization for the obtained results of Omicron sentiment prediction is depicted in Fig. 6, which describes the count of tweets for every predicted sentiment along timeline of data gathering based on posting date of these tweets. Also, it shows the time frame for our data on Omicron. More depiction is shown in Fig. 7 which highlights each sentiment by considering the number of tweets for each posting date in the form of column charts. Furthermore, Fig. 8 of the Pie chart presents the average percentage for each predicted sentiment toward Omicron virus.

Yet, the number of studies that have performed sentiment understanding for Omicron variant is very limited and especially studies that utilize deep learning techniques. The performance of the proposed framework has been compared with the performance of several sentiment analysis studies to validate the architecture of the proposed model and the performance of the entire introduced framework, see Table 2. Consequently, from the undertaken comparison in Table 2, it can be noticed that the deployed model based on Bi-LSTM and deep neural network layers (DNNs) has gained a high accuracy in comparison with recent studies.

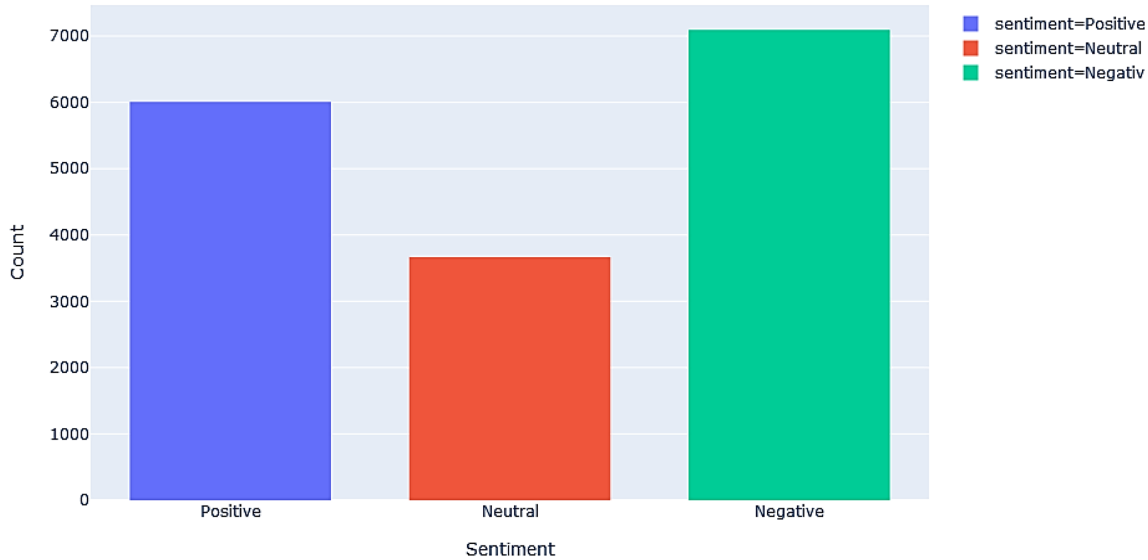


Fig. 5 Results of sentiment prediction on Omicron Twitter dataset

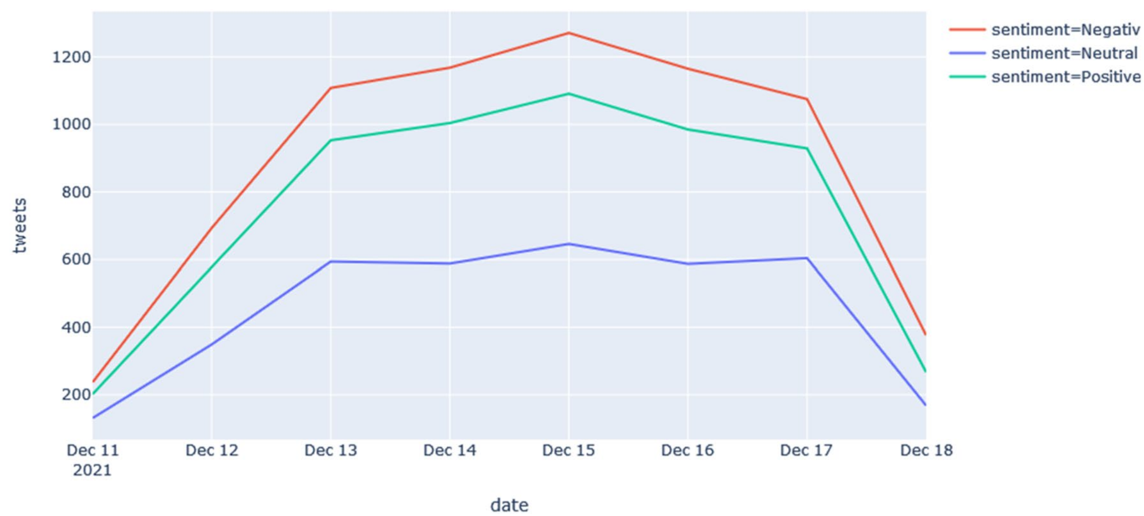


Fig. 6 Omicron emotion predication in related to timeline of collecting data

5 Conclusion

The discovery of the Omicron strain of COVID-19 in South Africa and area of Botswana at the end of November 2021 was soon characterized as an issue of concern by the World Health Organization (WHO). Later 46 US states and over 90 other countries have both reported finding Omicron. The epidemiologists claim that this kind of virus can significantly evade the immune system and is more infectious than the Delta form. However, the topic of Omicron virus fastely becomes a subject of discussions on social media that revealed lots of fears and anxiety feeling because of its infection and rapid spreading between humans that could exceed the delta infection. Thus, this study deployed a model for sentiment prediction toward Omicron virus utilizing data gathered from platform of Twitter for the time frame 11-Dec.-2021 to 18-Dec.-2021. In order to recognize the general public sentiment on the issue of the Omicron virus to help health and humanitarian organizations to deal with matters that could influence people's life from several aspects. As a result, the obtained outcomes from sentiment system

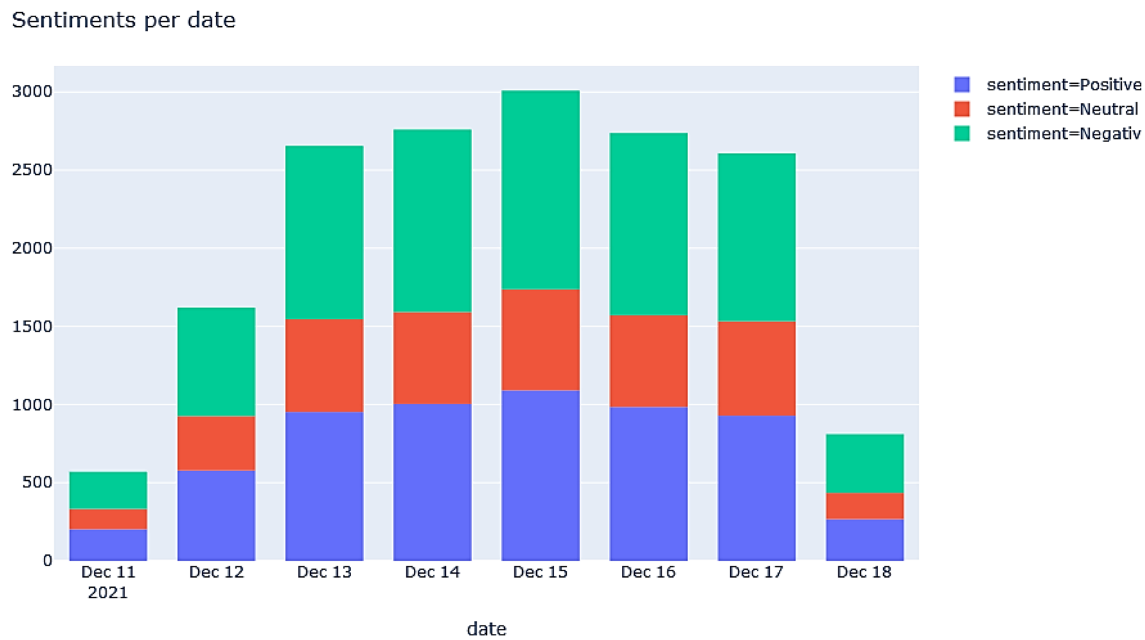
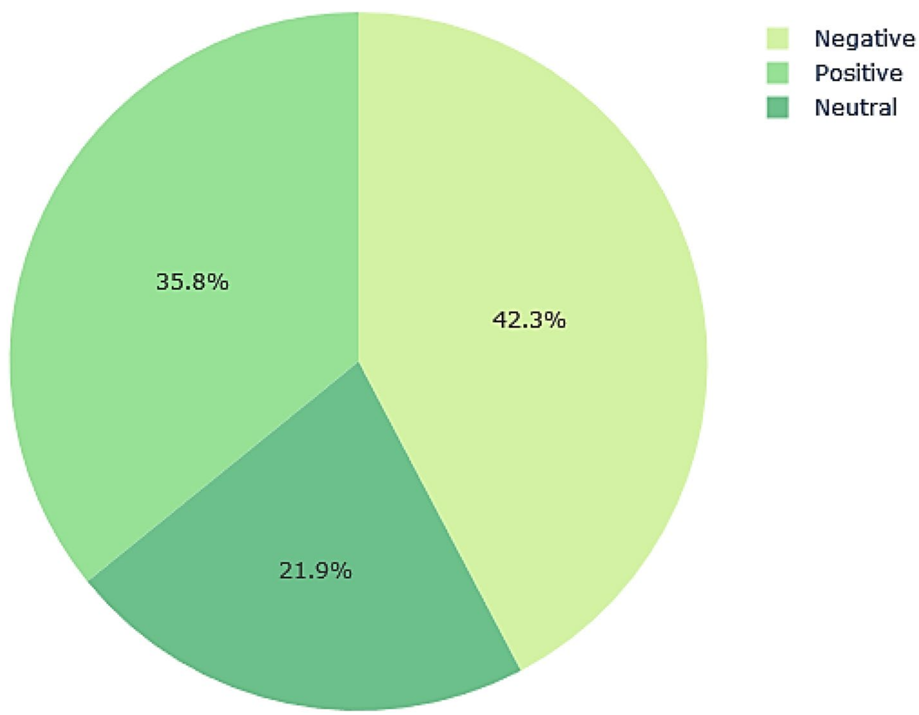


Fig. 7 highlights Omicron sentiment for each posting date

Fig. 8 The average percentage for each predicted sentiment toward Omicron virus



implementation showed Negative sentiment at 42.3%, Positive sentiment at 35.8%, and Neutral sentiment at 21.9%. This research can be extended for future work by improving the accuracy via exploring different models architectures and deep neural networks. Also, additional dataset could be applied for training and predication.

Table 2 Comparison with state-of-the-art studies based on the accuracy

Study	Technique	Accuracy Average
Long et al. (2019)	CNN network and LSTM	0.83%
Ismail et al. (2022)	BERT model-based ensemble stacking	0.8310
Alam et al. (2021)	Bi-LSTM framework	0.9083%,
The proposed method based on Bi-LSTM with DNNs		0.946%

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Data availability The datasets of the model construction used during the current study are available in the Kaggle repository, https://www.kaggle.com/ under the same mentioned names. The dataset of the prediction stage was collected during the current study and it is available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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