TEM Journal. Volume 13, Issue 2, pages 1470-1480, ISSN 2217-8309, DOI: 10.18421/TEM132-61, May 2024.

Deep Sentiment Analysis System with Attention Mechanism for the COVID-19 Vaccine

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***Abstract* – Sentiment analysis has attracted huge interest, which has been a trend topic in last years. It has significant applications in several areas, such as marketing based on opinion recognition and mining, movie reviews, product reviews, and healthcare-based sentiment understanding. In this paper, COVID-19 vaccine has been considered as an experimental design and performs sentiment analysis to understand the opinions of the public toward getting vaccinated. The topic of vaccination has been associated with a great deal of hesitancy and different points of view from people who may trust or distrust taking the vaccine.**

The proposed system aims to understanding data from chats related to the COVID-19 vaccine on the Twitter platform. A deep learning framework has been built based on a bidirectional long-short-term memory (Bi-LSTM) network and use an attention mechanism to obtain precise results. Three categories are used to classify the obtained results as positive, negative, neutral. The overall accuracy of the proposed method is found to be 94%, in addition accuracy of our case study results show for the three opinion mining classes of negative, neutral, and positive on the training set was 0.96%, 0.89%, and 0.95%, respectively. On the test data, the accuracy was 0.96% for negative sentiment, 0.88% for neutral sentiment, and 0.95% for positive sentiment.

***Keywords* – COVID-19, COVID-19 vaccine, SARS-COV-2 vaccine, Bidirectional LSTM, Attention mechanism.**

DOI: 10.18421/TEM132-61
https://doi.org/10.18421/TEM132-61

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Received: 14 November 2023.
Revised: 29 February 2024.
Accepted: 07 March 2024.
Published: 28 May 2024.

1. Introduction

Sentiment analysis based on NLP is a method of semantically analyzing and mining human-generated text containing opinions, in order to estimate the implied sentiment. This type of analysis has attracted strong interest and has become an important research trend in recent years, and represents an important artificial intelligence task in the area of text mining and recognition. Text-mining-based sentiment understanding has significant applications in several areas, such as marketing-based opinion recognition and mining, movie reviews, product reviews, and healthcare-based sentiment understanding [1], [2], [3].

For example, companies can take advantage of sentiment understanding to investigate people's opinions on the reputation of a brand, the experiences of customers, and the effects of social media. Most people today tend to read reviews of a product before buying it, and will make a decision based on the sentiment expressed about the item.

Sentiment analysis based on NLP is closely associated with other tasks such as emotion understanding, text mining, sentiment mining, and sentiment understanding, due to its relationship with textual information mining and retrieval. The main aim of sentiment mining is to identify public opinion expressed in the form of text on a particular topic, by classifying the textual information in the sentences or documents into negative, neutral, and positive as three classes. The healthcare field has taken advantage of the use of sentiment analysis to determine people's emotions toward issues related to human health, such as the events of the last few years involving the COVID-19 pandemic and vaccination for this disease. In this paper, we consider the COVID-19 vaccine as an experimental study and perform sentiment analysis to understand the opinions of the public toward getting vaccinated. The topic of vaccination has given rise to a great deal of hesitancy and different points of view from people who trust or distrust taking the vaccine [4], [5], [6], [7]. A rich source of data in social media platforms are for obtaining real-time insights into public feelings and opinions, which can be used to overcome these issues [8]. Individuals using social media have been rising rapidly in recent years, and one network that is expanding and gaining popularity globally is Twitter. It serves as a venue for people to share their thoughts on various topics, and plays an important part in distributing news around the world [9], [10], [11]. During the COVID-19 pandemic, knowing people's thoughts and behaviors was critical in order for the government to act in the most effective possible way to motivate people to get vaccinated against COVID-19 [12], [13], [14].

Sentiment analysis methods have been suggested based on machine learning approaches and various techniques such as the bag-of-words model and the naïve Bayes probabilistic model, and often require manual feature extraction. Social media text posts are varied and short, which makes the task of capturing features and classifying text a challenging matter. There is therefore a need for a more efficient method of sentiment recognition and estimation from short pieces of text. Deep learning (DL) approaches have shown outstanding performance in many computing domains. These approaches aim to learn the characteristics of data via neural networks with a deep hierarchal structure, such as convolutional neural networks (CNNs), which learn local features (spatial features) from phrases or words, and recurrent neural networks (RNNs), which learn long-term dependency features from sequences of data (temporal features) [15], [16]. However, the short pieces of text posted on the Twitter platform suffer from limitations in terms of feature extraction, and an embedding process has therefore been widely applied to distributed representation of a word for effective feature extraction based on the concept of word2vec [17].

Numerous techniques have been proposed and explored for sentiment analysis applications. One model based on a Bi-LSTM network for sentiment mining from textual comments achieved an F1-score of 92% [18]. A method of sentiment classification was developed based on one million tweets collected on five topics, using a hybrid combination of techniques from text mining and DL-based deep neural networks and RNNs, and was shown to have an accuracy of 83.7%. Several sentiment analysis studies have been carried out since 2020 with regard to the COVID-19 vaccine, with the aim of helping heath organizations to understand public opinion toward the topic of vaccines. One such study [19] utilized the K-nearest neighbors (KNN) method for sentiment recognition, based on 10,000 Twitter posts using the Twitter API. The outcomes demonstrated that positive feelings were slightly more prevalent than negative. Another research study [20] gathered tweets from Japanese users posted between 1 August 2020 and 30 June 2021, and performed a sentiment analysis on the topic of vaccines. It was reported that negative feelings were dominant overall compared to positive feelings, and were connected with the incidence of death and infection. The authors of [21] considered 31,100 tweets in English, posted by Australian users from January to October 2020, containing hashtags related to the COVID-19 vaccine. Visualizing high-frequency word clouds and word token correlations was used to analyze tweets and attitudes toward COVID-19 vaccination were analyzed by built a latent Dirichlet allocation (LDA) model. Another research study [22] collected 6,000 tweets about the COVID-19 vaccine between 15 and 22 January 2021 to assess the opinions of Indonesian people, using the naïve Bayes algorithm and 'COVID-19 vaccine' as keywords. The study identified 3,400 negative tweets (56%) and more than 2,400 positive tweets (39%), with the remainder (1%) being neutral. A recent study [23] proposed a method to identify the opinions of the public on COVID-19 vaccinations by applying a sentiment analysis system to Twitter data based on deep LSTM and Bi-LSTM networks. The accuracy achieved by the LSTM model was 90.59%, and the Bi-LSTM model achieved 90.83%.

The data covered the duration from January 2021 to July 2021, and consisted of 125,906 tweets. However, their method has been submitted for performance improvement in the future. The authors of [24] introduced a combination of an LSTM and a gated recurrent neural network (LSTM-GRNN) as a model for sentiment analysis towards the COVID-19 vaccine. Their method achieved a very high overall accuracy of 95%. Similarly, the authors of [25] developed a method for vaccine sentiment analysis that relied on a combination of CNN and LSTM networks. The method was applied to 13,000 tweets and achieved an average accuracy of 0.83.

An unsupervised method based on Sentiment-Reasoner (VADER) and Valence-Aware-Dictionary and LDA techniques was proposed in [26], and the data used for prediction were composed of 75,665 posts collected over the period between 12 December 2020 and 2 July 2021. The results on Twitter for discussions related to COVID-19 vaccinations showed that positive sentiment was predominant. The work in [27] used Tweepy to undertake an analysis of sentiment in Twitter posts relating COVID-19 vaccination. Similarly, the researchers in [28] analyzed sentiment toward the COVID-19 vaccine using (NLP) algorithms based on polarity. Their method was applied to a dataset containing 230,623 unique tweets from the period between 16 December 2021 and 8 April 2021, and it was found that the dominant sentiment was negative.

The work in [29] presented transformer models for sentiment classification based on RoBERT and BERT, in addition to multi-task specific versions in which these techniques were stacking with support vector machine (SVM) as a meta learner and combined using majority voting (MV). The highest accuracy obtained from this approach was 0.8310, based on an ensemble with stacking. The method proposed in [30] used the Bi-LSTM technique to carry out sentiment mining from Twitter posts relating to the COVID-19 vaccination, and achieved an accuracy of 74.92%. The authors note that their method could be further enhanced.

Although many researchers have conducted sentiment analysis studies with regard to the COVID-19 vaccine, performance improvements are needed [17], [18], [19], [20], [21]. In addition, much of the previous research on COVID-19 vaccine sentiment analysis has been carried out over different periods, and some studies have been undertaken only for a particular country [1].

The following key points explained the main contributions of this research:

- Develop a sentiment analysis system for the COVID-19 vaccine, which can aid in recognizing public sentiment towards getting vaccinated against the COVID-19 virus.
- The utility of deep learning techniques and NLP have been investigated to carry out data analysis and predict sentiment as positive, neutral, and negative, using text data retrieved from the Twitter social media platform.
- We deploy a deep learning model with a deep neural network architecture based on a Bi-LSTM network.
- We introduce a scaled dot-product attention mechanism to enhance the Bi-LSTM ANN in term of performance in order to obtain correct, precise predictions.
- We collect data from the Twitter platform using a data extraction API on the topic of the COVID-19 vaccine.
- We perform data scraping for the time period from 1 January 2021 to 3 September 2021.
- The proposed system can assist healthcare private and governmental sectors to understand the factors that make people hesitant to take the vaccine, so they can work on solving them.

The last section of the paper is segmented into key Sections 2, 3, and 4 which represent the proposed method, results, and summary of the paper respectively.

2. Proposed Methodology

In this work, the focus was on the use of deep learning NLP techniques. The proposed method consists of two phases: the model building phase and model execution phase. Figure 1 shows a diagram of our framework, which includes the following steps:

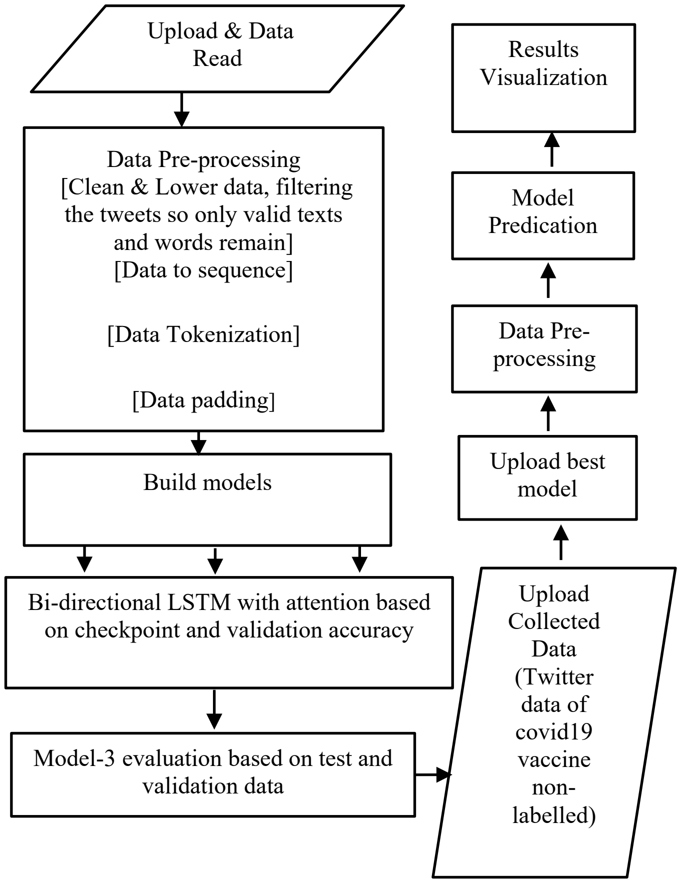

Figure 1. Framework of the proposed opinion mining system for the COVID-19 vaccine

- The first stage, once the data have been uploaded and read, is pre-processing, in which the data are cleaned to remove numbers, hyperlinks, punctuation, and certain specific characters that are not needed in the construction of the proposed model. We then apply data reduction and eliminate stop words, such as researches and prepositions, which may not relate to the results of this project. Then calculate the maximum length of the input tweet phrases that will be tokenized and padded.
- After data cleaning, tokenization and sequence padding are performed. Tokenization is a process in which text information is divided into words (tokens) by taking into account boundary markers such as commas, white space, quotation marks, semicolons, and periods as full stops. Single words may be tokens of a given type (verbs, nouns, pronouns, articles, conjunctions, prepositions, alphanumeric symbols, punctuation, and numbers). The list of tokens can be assigned for further processing. To carry out this process, we adopted Tokenizer, a deep learning Python library from Keras. A post-padding technique was applied to equalize the length of the input after tokenization.
- When the cleaned input text has undergone tokenization and padding, a set of numbers is output. This is because neural networks can only operate on numbers, which are the native language of computers. The next step is to encode the sentiment words as integers, where "neutral" is coded as zero, "negative" as one, and "positive" as two. Only legitimate, pertinent sentences and words remain when the pre-processing stage is complete, and the network is applied to these.
- The training and testing datasets as input is separated after pre-processing the data, with the test set accounting for 33% of the total data.
- We then used Bi-LSTM with an attention mechanism to construct a deep learning model. The suggested model architecture contains the input layer, an embedding layer, and a dropout layer, followed by the Bi-LSTM layer, another dropout layer, and an attention layer. Two dense layers are used: the first applies the ReLu activation function, while the second consists of a softmax classification layer, which is used to obtain sentiment predictions from the input tweets which have been categorized positive, negative, and neutral as into three groups.

2.1. Embedding Layer

The initial layer of the proposed model represents the input layer and the shape of the input is defined based on the max length of a sentence in the text or document. An embedding layer symbolizes the words in a document as a vector of integers that can be used to detect the context of words in a text [31].

In this study, the Keras library-based embedding layer was used to convert words into vectors. An integer input is sent to the embedding layer, which searches the internal dictionary to produce an association of dense vector. In a similar way to the training process of ANN, the embedding layer's initial weights are generated at random, and the word vectors are gradually changed using the backpropagation algorithm.

Maximum sentence length in the input sequence (max-len) was set to 120 in this study, and represents the length of the input passed to the embedding layer in this work. The embedding dimension was set to 64. A matrix of words in vector form represents the result of the embedding layer, and is passed to the dropout layer, the next layer in the proposed architecture.

2.2. Dropout Layer

Since the dropout technique is able to detect more randomness, it is used to prevent overfitting [31], [32]. The dropout layer is applied here as a solution to the issue of overfitting; in this layer, some neurons are randomly selected and given a value of zero, meaning that their input and output properties will be ignored. Two dropout layers are used in our model architecture, with a dropout rate of 0.8%.

The Bi-LSTM layer (before the attention layer) is applied prior the first dropout layer, and the second after. The next layer of the proposed model architecture is the Bi-LSTM.

2.3. Bi-LSTM Network

Bi-LSTM operates in both directions ANN made up of LSTM units in order to integrate the contextual data before and after a specific word. Bi-LSTM is able to learn dependencies over the long term, without storing duplicates of context information.

For text classification, it therefore gives good performance for sequence modelling and is commonly used. Bi-LSTM works in two layers and parallel manner, in both the backward and forward directions, to detect dependencies in both contexts [32], [33], unlike the LSTM network.

2.4. Attention Mechanism

In general, standard NLP models are unable to accurately process long input sequences, since they consider only the last hidden state for the last input sequence. The standard NLP model does not take into account the context of the input sequence with words from input sequence long memory which may give more relevant information that could support producing correct results than the last words.

The attention mechanism is used to enhance the performance of NLP techniques on various topics. This mechanism concentrates on distinctive parts when processing a long sequence by gathering relevant information from different parts of the input sequence and using them to predict precise outcomes [34], [35].

The attention mechanism is introduced to improve the Bi-LSTM model in this research, and the intermediate vector is replaced with a sequence of vectors. This means that the model no longer needs to compress all of the information into a fixed-dimensional vector, considerably reducing the original model's concerns with incomplete information representation, information dilution, and coverage.

The attention mechanism represents the features of the input sentence semantically. A scaled dot-product attention layer is used in our work that can be defined to an output as mapping inquiry and key-value pairs set. The main steps in the attention network are as follows. A similarity function based on the dot product is used to calculate the inquiry weights and keys.

A scaling operation is performed to calculate the factor $\sqrt{d_K}$ which plays a moderating role by minimizing the dot product. The weights obtained via the softmax function are normalized. The key-value V and similarity are computed to find the weighted summation as equal value [32]. The formula for the above steps can be represented as shown in Equation (1):

$$\text{Attention}(Q, K, V) = \left(\frac{Q\,K^T}{\sqrt{d_K}}\right) V \qquad (1)$$

2.5. Dense Layers and Model Fitting

We use two dense layers to gather sequence characteristics and classify these features into sentiments (positive, negative, or neutral). The first dense layer utilizes the ReLU activation function and has 64 dimensions, while the second one utilizes the softmax activation function to identify text and assess sentiment, as shown in Figure 2. The following equation is used to define softmax layer as:

$$P\left(\frac{z}{z}\right) = \text{softmax}(w^s h_k + b^s) \qquad (2)$$

$$z = \text{argmax}\left(p\ \left(\frac{z}{x}\right)\right) \qquad (3)$$

To perform model training, the model is compiled using loss-function based on “categorical cross-entropy”, the “Nadam” algorithm of optimization is adopted to enhance the optimizer and reduce the loss error. We use 16 epochs for model fitting.

2.6. Data Preparation

Previous research has shown that social media platforms can be valuable in understanding the attitudes of the public towards a specific topic [36], [37], [38], [39], [40]. In this research, we considered the Twitter social media platform and collected chat data (tweets) on the COVID-19 vaccine using the Snscrape tool library from Python. The data that were scraped for a generic geo-tag and time-frame mainly covered the period from 1 January 2021 to 3 September 2021.

The keywords used to pull data from Twitter were as follows: COVID-19 vaccination, Oxford, AstraZeneca, Moderna COVID-19 vaccine, COVID-19 vaccine risks, COVID-19 vaccine side effects, Pfizer, and Sinovac.

The total set of scraped data included in this work consisted of 121,761 unique tweets from 131,009 tweets after removing the duplicates. Only tweets in English were considered.

The data obtained from Twitter had no sentiment labels for use in training the model. Furthermore, since the amount of cleaned data was so large, labelling them would have taken a long time. The model proposed in this study requires a large amount of labelled data for training due to using a supervised deep learning model.

To overcome this issue, we built on previous research [41] by employing popular annotated datasets from Twitter for the deployment of our sentiment analysis model. Four datasets were used to train the model: the Tweet extraction dataset, the Airline sentiment dataset, the Apple tweeter sentiment dataset, and the Twitter-and-Reddit-sentiment-analysis datasets, all of which are publicly available from the Kaggle repository and are annotated with three different classes of sentiment (positive, negative, and neutral).

These datasets were combined to give a total of tweet samples (358,897), after removing data featuring “NULL”, and “NAN” entries and eliminating duplicate tweets. The training and validation processes were carried out on this generated dataset.

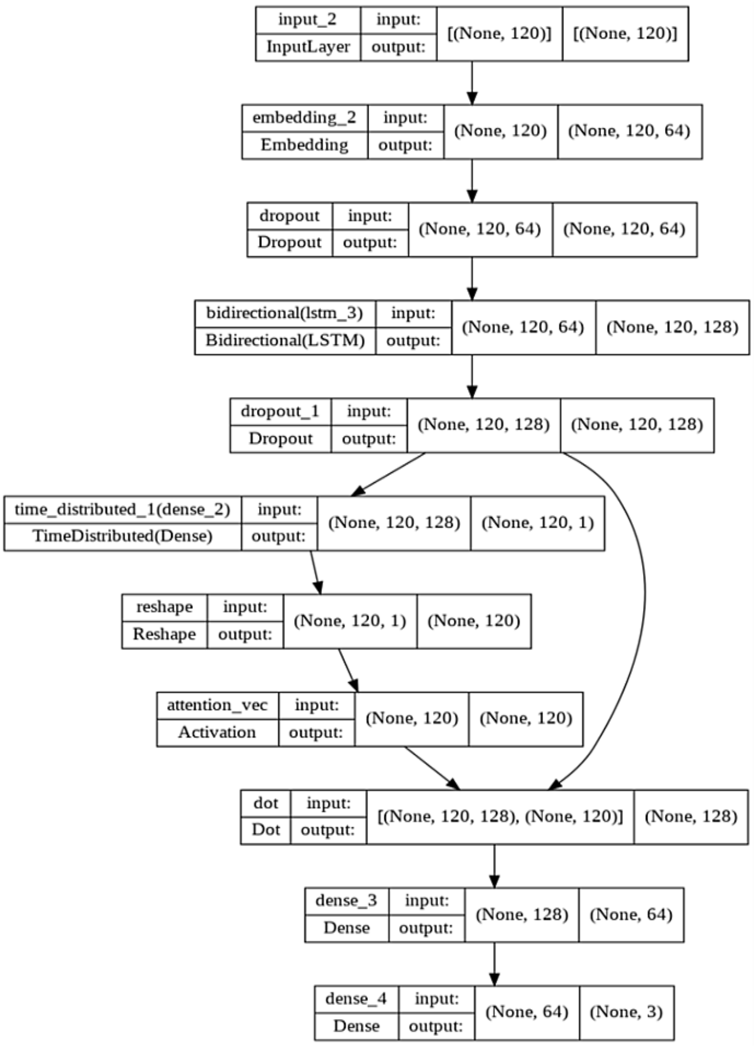

Figure 2. The proposed Bi-LSTM model with attention mechanism

3. Results and Analysis

In this research, we present a system that can perform sentiment understanding, based on an attention mechanism with a Bi-LSTM ANN, when implemented to data scraped from the Twitter platform. The derived data from posts on the Twitter platform during the period 1 January 2021 to 3 September 2021 is considered here for prediction and analysis, using the Snscrape tool from the Python library. The proposed method was designed in the Python 3.7 programming language, and was based on NLP algorithms.

The Keras and TensorFlow libraries were used for construction of the model based on the Google Colab GPU. The dataset used to train the model, as explained in the previous section, contained tweets (358,897) after cleaning process. The data were randomly split into a training dataset (containing 67% of the samples) and a test dataset (containing 33% of the samples) is used for the training process. A validation dataset (20% from total samples) and a test dataset (13% of the total samples) as the test data were further split. To measure the accuracy, ModelCheckpoint Keras is used for an evaluation metric. Callbacks for saving the model using the best validation accuracy, in the form of .h5 file.

For both training and validation sets, Figure 3 shows the results from the model training process in terms of the accuracy and loss errors.

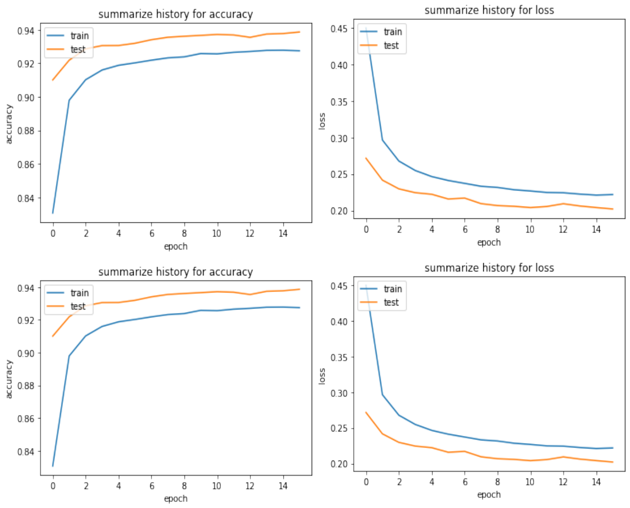

Figure 3. Results for the accuracy and loss error in the training phase

The confusion matrix for each predicted sentiment was computed for the training and test datasets. On the training dataset, the accuracy achieved was 0.96, 0.89, and 0.95 for the negative, neutral, and positive sentiment classes, respectively; while Figure 4 shows the test dataset the results were 0.96, 0.88, and 0.95,.

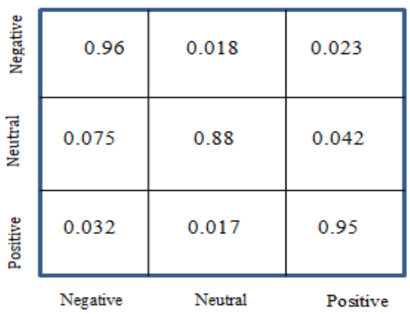

Figure 4. Confusion matrix for the test data

To assess the performance of our model, Table 1 presents a comparison was performed based on the accuracy metric with other related works methods. The Bi-LSTM with an attention mechanism represents the suggested model achieved better accuracy than the other methods. Our model is also fast, and has an attention layer to ensure correct results.

Table 1. Comparison with recent studies based on accuracy metric

Ref.	**Technique**	**Average accuracy**
[16]	Bi-LSTM	0.9083
[18]	CNN+LSTM	0.83
[22]	BERT-based ensemble stacking	0.8310
[23]	Bi-LSTM	0.7492
Proposed	Bi-LSTM with attention	0.94

After the training and fitting phase, the model was applied to the vaccine-related data gathered from Twitter. First, a CSV file containing Twitter data on the COVID-19 vaccines was uploaded and read, and NLP algorithms were used to carry out data pre-processing. Data were cleaned by removing tweets that were not in English, those that contained NAN fields, and those with empty words (nowords). Frequent tweets were eliminated to avoid any confusion and blur. In the next step, data cleaning was performed, following the same pre-processing procedure as in the training stage, by eliminating linked addresses, URLs, email addresses, digits, punctuation, and other non-relevant characters. The cleaned data were then transformed into sequences. In the next step, to make the data suitable for the prediction stage, data tokenization and pad-sequence operations were executed.

The proposed Bi-LSTM model with attention was then used to make sentiment predictions. The results are visualized below to illustrate the outcomes. A timeline and the number of tweets in each class in relation to the date of posting are stated in Figure 5. It can be seen that the dominant sentiment for the period from 1 January 2021 to 3 September 2021 was neutral. Figure 6 shows the results, and such figure can be noted that the predominant sentiment was neutral, with the highest percentage (72.77%) for all of the data gathered on vaccines; the negative sentiment was the next highest (17.52%), and the positive sentiment was last (9.69%) for the selected time interval.

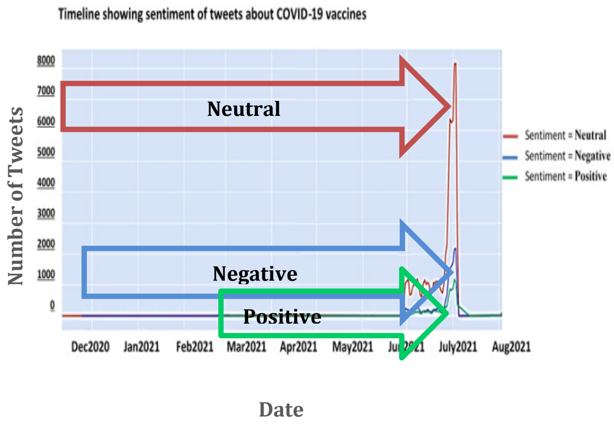

Figure 5. Timeline and sentiment of Tweets about the COVID-19 vaccines

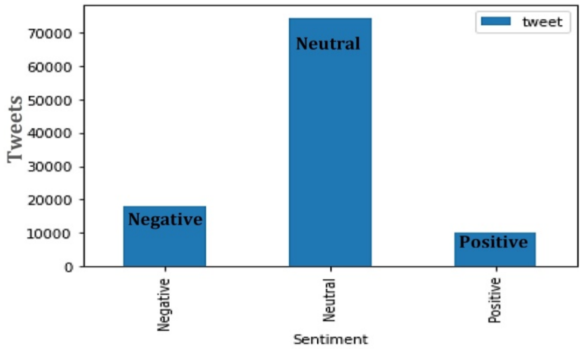

Figure 6. Sentiment prediction results for COVID-19 vaccine Tweets

Figures 7–10 show the findings of the sentiment analysis in relation to certain COVID-19 vaccines, including those made by Pfizer, Moderna, Sinovac, and AstraZeneca. The graphs display the number of tweets identified by the prediction method for each sentiment. It can be seen that tweets with a neutral sentiment were most numerous, and tweets with a negative sentiment were the second most frequent. Tweets with a positive sentiment were fewest.

It can be seen from the results for the neutral sentiment that most people were hesitant to take the vaccine, and their opinion was neither yes nor no, meaning that they were waiting to see what would happen. The results for the second category (negative) indicate that a large number of people refused to be vaccinated because they thought that the vaccine might have a detrimental effect on their health in the future. The results for the third category (positive) reveal that some people accepted the vaccine and considered it a life saver that could prevent harm and death from COVID-19. Our system enables people's emotions to be identified and their opinions on the COVID-19 vaccine to be mined, thus allowing governments and healthcare organizations to benefit by taking into account these rates and numbers throughout the data collection period, and allowing them to take action to prevent difficulties that may affect people or make them hesitant to take the vaccine.

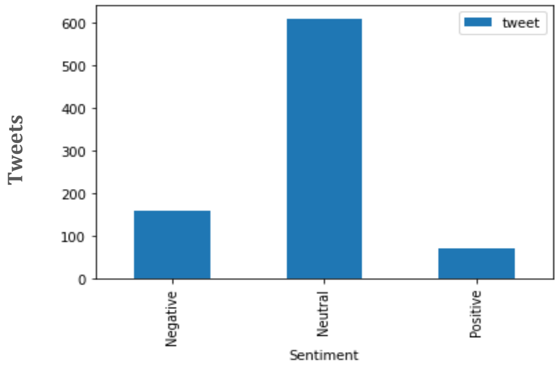

Figure 7. The sentiment analysis findings for Tweetson the Pfizer vaccine

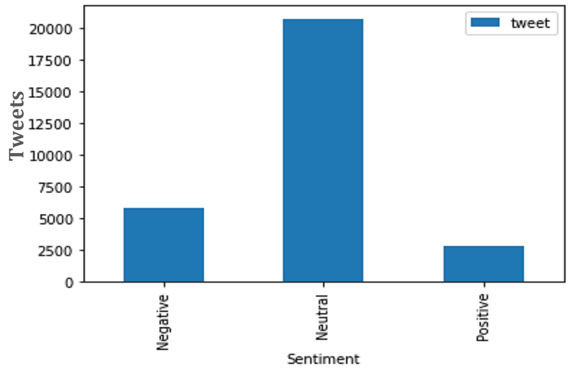

Figure 8. The sentiment findings analysis for Tweets on the Sinovac vaccine

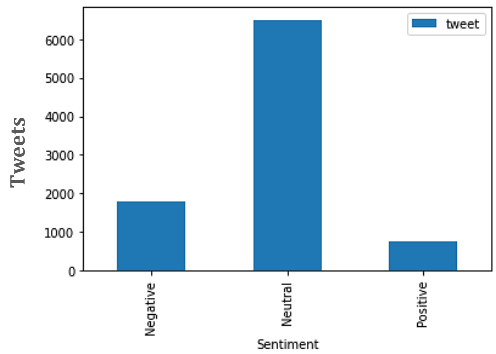

Figure 9. Results of the sentiment analysis for Tweets on the Moderna vaccine

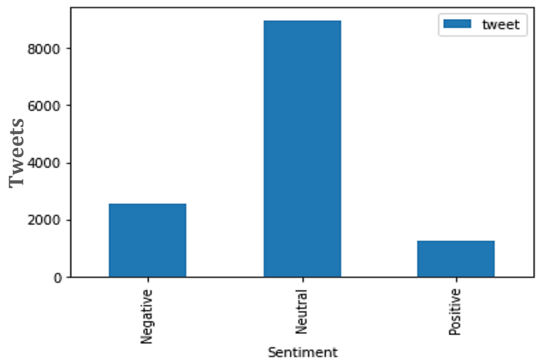

Figure 10. Results of the sentiment analysis for Tweets on the AstraZeneca vaccine

4. Conclusion

Paper has presented a sentiment understanding study in which we examined chat data about the COVID-19 vaccination taken from Twitter over the period 1 January 2021 to 3 September 2021. The suggested model combined a deep Bi-LSTM neural network with an attention mechanism, and gave good results. The outcomes at the model training and validation stages showed high accuracy for all three sentiment classes. Based on test data, the total accuracy for the generated model was 0.94, which was higher than other COVID-19 vaccine sentiment analysis models. The results from applying the final model to the data collected from Twitter showed that the prominent sentiment of the public toward the COVID-19 vaccine over this period was neutral (72.77%), while a negative sentiment was found in a low proportion of tweets (17.72%) and a positive sentiment was the lowest (9.69%). The sentiment analysis method suggested in this study was found to be effective in terms of analyzing large amounts of data, and can be applied to other topics. In the future, we intend to investigate and/or combine other neural networks to improve the precision of the model, and to consider more data at the model training stage. We also intend to design a more robust data pre-processing procedure.

Acknowledgements

This study is supported by Natural Science Foundation of Top Talent of SZTU (grant No. 20211061010016).

References:

[1]. Liu, H., Chatterjee, I., Zhou, M., Lu, X. S., & Abusorrah, A. (2020). Aspect-Based Sentiment Analysis: A survey of deep learning methods. *IEEE Transactions on Computational Social Systems*, *7*(6), 1358–1375. Doi: 10.1109/tcss.2020.3033302.

[2]. Zucco, C., Calabrese, B., Agapito, G., Guzzi, P. H., & Cannataro, M. (2019). Sentiment analysis for mining texts and social networks data: Methods and tools. *WIREs Data Mining and Knowledge Discovery*, *10*(1). Doi: 10.1002/widm.1333.

[3]. Khalefa, M. S., Abduljabar, Z. A., Zeki, H. A., & Al-Arab, S. (2011). Fingerprint image enhancement by develop Mehtre technique. *Advanced Computing : An International Journal*, *2*(6), 171–182. Doi: 10.5121/acij.2011.2616

[4]. Gohil, S., Vuik, S., & Darzi, A. (2018). Sentiment Analysis of health care tweets: Review of the methods used. *JMIR Public Health and Surveillance*, *4*(2), e43. Doi: 10.2196/publichealth.5789

[5]. Jelodar, H., Wang, Y., Orji, R., & Huang, S. (2020). Deep sentiment classification and topic discovery on novel coronavirus or COVID-19 online discussions: NLP using LSTM Recurrent Neural Network Approach. *IEEE Journal of Biomedical and Health Informatics*, *24*(10), 2733–2742. Doi: 10.1109/jbhi.2020.3001216

[6]. Nyangaresi, V. O., Sibahee, M. a. A., Abduljabbar, Z. A., Ma, J., & Khalefa, M. S. (2022). Biometric-Based Packet Validation Scheme for Body area Network smart healthcare devices. *2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)*. Doi: 10.1109/melecon53508.2022.9842900

[7]. Nyangaresi, V. O., Abduljabbar, Z. A., Ma, J., & Al Sibahee, M. A. (2022). Verifiable Security and Privacy Provisioning Protocol for High Reliability in Smart Healthcare Communication Environment. In *2022 4th Global Power, Energy and Communication Conference (GPECOM)*, 569-574. IEEE.

[8]. Hussain, A., Tahir, A., Hussain, Z., Sheikh, Z., Gogate, M., Dashtipour, K., … Sheikh, A. (2021). Artificial intelligence-enabled analysis of public attitudes on Facebook and twitter toward COVID-19 vaccines in the United Kingdom and the United States: Observational study. *Journal of Medical Internet Research*, *23*(4), e26627. Doi:10.2196/26627

[9]. Chopra, H., Vashishtha, A., Pal, R., Tyagi, A., & Sethi, T. (2021). Mining trends of COVID-19 vaccine beliefs on Twitter with lexical embeddings. *arXiv preprint arXiv:2104.01131*.

[10]. Sattar, N. S., & Arifuzzaman, S. (2021). COVID-19 vaccination awareness and aftermath: Public sentiment analysis on Twitter data and vaccinated population prediction in the USA. *Applied Sciences (Basel, Switzerland)*, *11*(13), 6128. Doi:10.3390/app11136128.

[11]. Al-Sulami, Z. A., Hashim, H. S., Ali, N., & Abduljabbar, Z. A. (2023). Investigating the relationship between knowledge management practices and organizational learning practices in the universities' environment. *International Journal of Electrical and Computer Engineering (IJECE)*, *13*(2), 1680. Doi:10.11591/ijece.v13i2.pp1680-1688.

[12]. Lyu, J. C., Han, E. L., & Luli, G. K. (2021). COVID-19 vaccine-related discussion on Twitter: Topic modeling and sentiment analysis. *Journal of Medical Internet Research*, *23*(6), e24435. Doi:10.2196/24435.

[13]. Hu, T., Wang, S., Luo, W., Zhang, M., Huang, X., Yan, Y., … Li, Z. (2021). Revealing public opinion towards COVID-19 vaccines with Twitter data in the United States: Spatiotemporal perspective. *Journal of Medical Internet Research*, *23*(9), e30854. Doi:10.2196/30854.

[14]. Jameel, A. S. (2020, November). The role of information and communication technology on knowledge sharing among the academic staff during COVID-19 pandemic. In *2020 2nd Annual International Conference on Information and Sciences (AiCIS)* (pp. 141-147). IEEE.

[15]. Melchior, J., Wang, N., & Wiskott, L. (2017). Gaussian-binary restricted Boltzmann machines for modeling natural image statistics. *PloS one*, *12*(2), e0171015.

[16]. Jalil Jassim Ghrabat, M., Alaa Hussien, Z., S. Khalefa, M., Ameen Abduljabbar, Z., Omollo Nyangaresi, V., A. Al Sibahee, M., & Wahab Abood, E. (2022). Fully automated model on breast cancer classification using deep learning classifiers. *Indonesian Journal of Electrical Engineering and Computer Science*, *28*(1), 183. Doi:10.11591/ijeecs.v28.i1.pp183-191.

[17]. Wang, J. H., Liu, T. W., Luo, X., & Wang, L. (2018, October). An LSTM approach to short text sentiment classification with word embeddings. In *Proceedings of the 30th conference on computational linguistics and speech processing (ROCLING 2018)*, 214-223.

[18]. Abd El-Jawad, M. H., Hodhod, R., & Omar, Y. M. (2018, December). Sentiment analysis of social media networks using machine learning. In *2018 14th international computer engineering conference (ICENCO)*, 174-176. IEEE.

[19]. Mehedi Shamrat, F. M. J., Chakraborty, S., Imran, M. M., Muna, J. N., Billah, M. M., Das, P., & Rahman, M. O. (2021). Sentiment analysis on twitter tweets about COVID-19 vaccines usi ng NLP and supervised KNN classification algorithm. *Indonesian Journal of Electrical Engineering and Computer Science*, *23*(1), 463. Doi:10.11591/ijeecs.v23.i1.pp463-470.

[20]. Niu, Q., Liu, J., Kato, M., Shinohara, Y., Matsumura, N., Aoyama, T., & Nagai-Tanima, M. (2022). Public opinion and sentiment before and at the beginning of COVID-19 vaccinations in Japan: Twitter analysis. *JMIR infodemiology*, *2*(1), e32335.

[21]. Kwok, S. W. H., Vadde, S. K., & Wang, G. (2021). Tweet Topics and Sentiments Relating to COVID-19 Vaccination Among Australian Twitter Users: Machine Learning Analysis. *Journal of medical Internet research*, *23*(5), e26953. Doi:10.2196/26953.

[22]. Pristiyono, Ritonga, M., Ihsan, M. A. A., Anjar, A., & Rambe, F. H. (2021). Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm. *IOP Conference Series. Materials Science and Engineering*, *1088*(1), 012045. Doi:10.1088/1757-899x/1088/1/012045.

[23]. Alam, K. N., Khan, M. S., Dhruba, A. R., Khan, M. M., Al-Amri, J. F., Masud, M., & Rawashdeh, M. (2021). Deep learning-based sentiment analysis of COVID-19 vaccination responses from Twitter data. *Computational and Mathematical Methods in Medicine*, *2021*, 4321131. Doi:10.1155/2021/4321131.

[24]. Reshi, A. A., Rustam, F., Aljedaani, W., Shafi, S., Alhossan, A., Alrabiah, Z., … Ashraf, I. (2022). COVID-19 vaccination-related sentiments analysis: A case study using worldwide Twitter dataset. *Healthcare (Basel, Switzerland)*, *10*(3), 411. Doi:10.3390/healthcare10030411.

[25]. Nuser, M., Alsukhni, E., Saifan, A., Khasawneh, R., & Ukkaz, D. (2022). Sentiment analysis of COVID-19 vaccine with deep learning. *J Theor Appl Inf Technol*, *100*(12), 4513-4521.

[26]. Yin, H., Song, X., Yang, S., & Li, J. (2022). Sentiment analysis and topic modeling for COVID-19 vaccine discussions. *World Wide Web*, *25*(3), 1067–1083. Doi:10.1007/s11280-022-01029-y

[27]. Chinnasamy, P., Suresh, V., Ramprathap, K., Jebamani, B. J. A., Srinivas Rao, K., & Shiva Kranthi, M. (2022). COVID-19 vaccine sentiment analysis using public opinions on Twitter. *Materials Today: Proceedings*, *64*, 448–451. Doi:10.1016/j.matpr.2022.04.809.

[28]. Sarirete, A. (2022). Sentiment analysis tracking of COVID-19 vaccine through tweets. *Journal of Ambient Intelligence and Humanized Computing*, 1–9. Doi:10.1007/s12652-022-03805-0.

[29]. Ismail, Q., Obeidat, R., Alissa, K., & Al-Sobh, E. (2022). Sentiment analysis of COVID-19 vaccination responses from twitter using ensemble learning. *2022 13th International Conference on Information and Communication Systems (ICICS)*. IEEE.

[30]. Khalid, E. T., Talal, E. B., Khamees, M. K., & Yassin, A. A. (2022). Sentiment analysis system for COVID-19 vaccinations using data of Twitter. *Indonesian Journal of Electrical Engineering and Computer Science*, *26*(2), 1156. Doi:10.11591/ijeecs.v26.i2.pp1156-1164.

[31]. Sangeetha, K., & Prabha, D. (2021). RETRACTED ARTICLE: Sentiment analysis of student feedback using multi-head attention fusion model of word and context embedding for LSTM. *Journal of Ambient Intelligence and Humanized Computing*, *12*(3), 4117–4126. Doi:10.1007/s12652-020-01791-9.

[32]. Long, F., Zhou, K., & Ou, W. (2019). Sentiment analysis of text based on bidirectional LSTM with multi-head attention. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 141960–141969. Doi:10.1109/access.2019.2942614.

[33]. Chandra, R., & Krishna, A. (2021). COVID-19 sentiment analysis via deep learning during the rise of novel cases. *PloS One*, *16*(8), e0255615. Doi:10.1371/journal.pone.0255615.

[34]. Lin, X.-M., Ho, C.-H., Xia, L.-T., & Zhao, R.-Y. (2021). Sentiment analysis of low-carbon travel APP user comments based on deep learning. *Sustainable Energy Technologies and Assessments*, *44*(101014), 101014. Doi:10.1016/j.seta.2021.101014.

[35]. Wang, S., Zhu, Y., Gao, W., Cao, M., & Li, M. (2020). Emotion-semantic-enhanced bidirectional LSTM with multi-head attention mechanism for microblog sentiment analysis. *Information (Basel)*, *11*(5), 280. Doi:10.3390/info11050280.

[36]. Praveen, S. V., Ittamalla, R., & Deepak, G. (2021). Analyzing the attitude of Indian citizens towards COVID-19 vaccine - A text analytics study. *Diabetes & Metabolic Syndrome*, *15*(2), 595–599. Doi:10.1016/j.dsx.2021.02.031.

[37]. Wang, B., & Zhuang, J. (2017). Crisis information distribution on Twitter: a content analysis of tweets during Hurricane Sandy. *Natural Hazards (Dordrecht, Netherlands)*, *89*(1), 161–181. Doi:10.1007/s11069-017-2960-x.

[38]. Buntain, C., Golbeck, J., Liu, B., & LaFree, G. (2021). Evaluating public response to the Boston Marathon Bombing and other acts of terrorism through Twitter. *Proceedings of the International AAAI Conference on Web and Social Media*, *10*(1), 555–558. Doi:10.1609/icwsm.v10i1.14774.

[39]. Chatfeld, A., & Brajawidagda, U. (2012). Twitter tsunami early warning network: a social network analysis of Twitter information fows. *23rd Australasian conference on information systems*, Geelong, Australia.

[40]. Paul S., Daniel C., & Guy, M. (2012). Twitter earthquake detection: earthquake monitoring in a social world. *Annals of Geophysics*, *54*(6). Doi:10.4401/ag-5364.

[41]. Basiri, M. E., Nemati, S., Abdar, M., Asadi, S., & Acharrya, U. R. (2021). A novel fusion-based deep learning model for sentiment analysis of COVID-19 tweets. *Knowledge-Based Systems*, *228*(107242), 107242. Doi:10.1016/j.knosys.2021.107242.