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SENTIMENT ANALYSIS OF COVID-19 VACCINE WITH DEEP LEARNING

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ABSTRACT

After the emergence of the Covid-19 virus, pharmaceutical companies began making vaccines against this virus. Peoples' reactions towards vaccines varies between acceptance and rejection. Information about these reactions can be found in social media which has become the largest and best source of users' opinions on a specific topic nowadays. One of the most important social media through which this data can be collected is Twitter. It is important to analyze people's opinions about these vaccines to find out the percentage of supporters and opponents of vaccines. Sentiments analysis can be used to analyze people's opinions. In this paper, we proposed a hybrid deep learning model to analyze user sentiment towards the COVID-19 vaccine. The contributions of our work are to adopt an efficient-designed model by combines Convolutional Neural Network (CNN), which has the capability to extract features, and Long Short-Term Memory (LSTM), which can monitor and study long-term dependencies between words. And provide the proposed network topology setting that contributed in producing high performance in sentiment analysis of the COVID-19 vaccine tweets. Extensive experiments have been conducted on a data set of 13,190 tweets. The results proved that the proposed model with the proposed topology setting outperformed the other machine learning models.

Keywords: *CNN-LSTM, Deep learning, Hybrid Model, Natural Language Processing (NLP), Sentiment Analysis.*

1. INTRODUCTION

In recent years, the number of social media users such as Facebook, Twitter, Instagram, etc. has become very large, as Kepios analysis shows that social media users reached in October 2021 4.55 billion users around the world [1]. A large number of users of different social networks share their opinions on various topics such as political, medical, and economic topics. User feedback is very important for companies and governments as it can be used to analyze users' opinions about a specific product or topic in order to assist them in the decision-making process. Hence the need for sentiment analysis also called opinion mining [2], which we can consider as a classification problem [3].

Sentiment analysis is the method at which positive or negative sentiment in text is detected. Usually, sentiments can be different depending on the cultures of people. Several research papers were published on Sentiment analysis [4-12] which investigated several areas such as crime [6], education [7], financial [8], marketing [9], political [10] and healthcare [11-12].

Covid 19 virus is a virus of corona family that was discovered in 2019 in China. After the discovery of the first infection with this virus, the number of infections and deaths due to the Covid 19 virus increased dramatically, until it reached all countries of the world. The Covid-19 has led to a global pandemic and loss of life as well as its great impact on the economy, social life, and human mentality [12]; so it is necessary to find quick solutions to an emergent epidemic of this type. Therefore, at the start of the pandemic, countries went into sweeping lockdowns and then imposed mandatory laws such as wearing masks and social distancing. After that, pharmaceutical companies around the world began producing vaccines against the Covid-19 virus, such as Pfizer [13], AstraZeneca [14], and Sinopharm [15]. However, it is important to analyze people's opinions about these vaccines to find out the percentage of supporters and opponents of vaccines

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in order to find ways and solutions to encourage communities to receive vaccines.

Therefore, in this research we propose to use Deep Learning (DL) algorithms with Natural Language Processing to classify people's opinions about Covid 19 vaccines into positive or negative. We will use CNN and LSTM networks to build a hybrid model for categorizing tweets obtained from Twitter. Deep learning is a part of machine learning that falls under the name of artificial intelligence, as the term deep learning began to be used in neural networks in the year 2000. Deep learning models are based on neural networks, where the model is learned at various levels of abstraction, hence the term "deep", which means that the model is learned in depth and at different levels. The difference between Machine Learning (ML) Neural Networks as it is called Artificial Neural Network (ANN) and Deep Learning Neural Networks (DNN) is that ANN has only 3 layers an input layer, a hidden layer, and an output layer, while DNN has more than 3 layers an input layer, at least two hidden layers, and an output layer.

In recent years, Deep Learning algorithms have become popular for sentiment analysis. The Deep Learning based techniques have mostly used Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) [16]. Therefore, this research will investigate the suitability of both techniques on covid-19 data in addition to building a hybrid model that combines both models and apply it for sentiment analysis.

1.1 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of the neural networks that were proposed in 1989 [17]. CNN is used to solve various problems, including image processing [18] due to the presence of convolution layers, text classification [19], object detection [20], etc. There are three types of CNN, the first 1D CNN is used to deal with texts, the second 2D CNN is used to deal with images, and the latter 3D CNN is used to deal with three-dimensional images. CNN's job basically boils down to receiving data, which may be in the form of images, text, numbers, audio, etc. Then the features are extracted from this data and finally the data classification stage.

As shown in Figure 1, in addition to the input and output layers, CNN consists of several main layers:

1. Convolutional Layer: The most important layer which is used to extract features from data by applying a specific filter to define the feature extraction mechanism. There are different types of filters.

2. Pooling Layer: used to reduce the dimensions of the derived attribute matrix to reduce the complexity of calculations. Max Pooling is one of the most popular Pooling types, as it uses a filter that turns into a 2 * 2 matrix by taking the largest value from each fraction, average or sum of the values, etc.

3. Fully Connected Layer: The input image from the previous layers are flattened (converted into one dimensional matrix) and fed to this layer through which all layers are linked to implement the classification process.

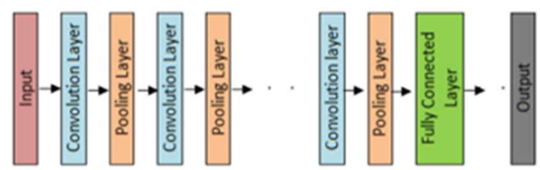

Figure 1. CNN structure [18]

1.2 Long short-term memory networks (LSTM)

Long short-term memory networks (LSTM) is an enhancement of recurrent neural network (RNN) appeared in 1997 [21], LSTM was suggested to solve a RNN problem which is vanish gradient. It was called the long memory because it retains the information for a long time. LSTM is used to solve various problems, including predicting traffic flow [22], Predicting Stock Prices [23], detection of congestive heart failure [24], useful for forecasting the time series [25], etc., As shown in Figure 2, LSTM consists of several main gates:

1. First, LSTM takes two inputs, output from the previous hidden state (ht-1) and current input (xt).

2. Input gate: It works to remove unwanted information and save important information.

3. Forget gate: Defines the information that must be discharged from the cell. The sigmoid activation function is used, and the result is 0 the information must be discharged and 1 the information must be preserved.

4. Output gate: It takes the values from the forget gate and applies on it the *tanh* activation function, and then determines the values that will be taken out for the next hidden layer.

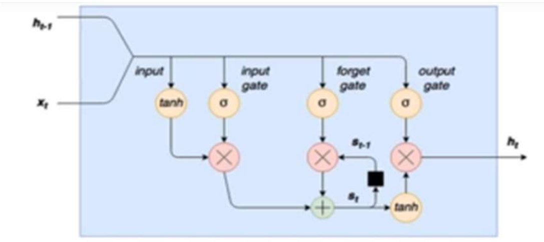

Figure 2 LSTM structure

2. LITERATURE REVIEW

In this section, a review of some research articles that are related to deep learning and machine learning techniques will be presented.

2.1 Deep learning

Ramadhani and Goo [26] proposed using the deep neural network (DNN) with three hidden layers in order to predict people's emotions. In their study, they used a data set of 4,000 records, and they processed this data by removing the symbols from each sentence and dividing it into tokens. Their proposed model achieved an accuracy of 75.03%.

Dang et al.,[27] performed a comparative study for sentiment analysis based on deep learning. They analyzed 32 papers and found that DNN, CNN, and hybrid approaches were identified as the most widely used models. They concluded that common techniques, such as CNN, RNN, and LSTM, are individually tested on datasets, and there is a lack of a comparative analysis for them. Baktha and Tripathy [28] compared three types of Recurrent Neural Network (RNN) (vanilla RNNs, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)). They applied these networks to three different datasets. The first dataset contains user reviews about personal care products on Amazon, the second dataset contains reviews about movies with five class label, and the last also contains reviews about movies but with 2 class label. The GRU network achieved the best performance in all three datasets.

Nguyen and Minh-Le Nguyen [29] proposed a hybrid model consisting of Deep Convolutional Neural Network (DeepCNN) with two wide convolution layers, and Bidirectional Long Short-Term Memory network (Bi-lSTM) to predict people's emotions and classify them into positive or negative. In their study, they used three datasets, which are Stanford, Sanders, and Health Care Reform. They processed this data by removing the stop words and remove special character from each sentence, but they retained the emoticon features in the dataset because deep learning has the ability to capture information from the emotion features to increase the accuracy of the model.

2.2 Machine Learning

Ritonga et al. [30] used the Naive Bayes (NB) algorithm to analyze Indonesian people's feelings about COVID-19 vaccines. In order to train their proposed model, they collected data through Twitter API using the "Vaccine COVID-19" as keywords. Their dataset includes 6000 records. They preprocessed data by breaking it into tokens and then returning each word to its root. Rating results using the NB model indicated that 39% had positive feelings about vaccinations, while 56% had negative feelings and 1% had neutral feelings.

Huq et al. [31] compared two machine learning algorithms (k-nearest neighbor (KNN) and support vector machine (SVM)) for classifying feelings. In their study, they used a dataset of 1,000 tweets. They trained these models with 5 features (n-gram feature, pattern feature, punctuation feature, keyword-based feature and word feature) in addition to normalize the data. The KNN model performed better than the SVM model in this study.

Wazery et al [32] compared Support Vector Machine (SVM), K- Nearest Neighbor (KNN), Naive Bayes, and Decision Tree with Long Short-Term Memory (LSTM) to categorize sentiment and opinions on Twitter into positive sentiment or negative, in terms of accuracy, precision, recall and f-measure. They used three databases on twitter which are IMDB, Amazon and Airline. The results showed that LSTM had achieved the highest accuracy at 88% for Amazon dataset, 87% for IMDB dataset and 93% for Airline dataset.

After the emergence of the Covid-19 virus, pharmaceutical companies began making vaccines against this virus. It is important to find a way to analyze and classify people's opinions about these vaccines. Several researchers study sentiment analysis on COVID-19 vaccine related topics. Lyu et al. [33] used the R software to perform topic modeling using Latent Dirichlet Allocation(LDA) on twitter data. The analysis revealed a positive sentiment about COVID-19 vaccines which may imply higher acceptance of COVID-19 vaccines compared with previous vaccines. Melton et. Al. further confirmed the positive sentiment using LDA topic modeling [34].

Hussain et al. developed an artificial intelligence–based approach to analyze public sentiments on social media in the United Kingdom and the United States toward COVID-19 vaccines. Results were in

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line with previous results which showed positive attitude over vaccine development and usefulness [35].

More concentration is needed on people's attitude toward COVID-19 vaccines in order to spread awareness among them. Therefore, in this paper, we aim to build a hybrid model using deep learning networks to analyze and categorize people's opinions. In addition, we will test the effectivity of hybrid deep learning networks at sentiment analysis

3. RESEARCH METHODOLOGY

The methodology used in this research is shown in Figure 3.

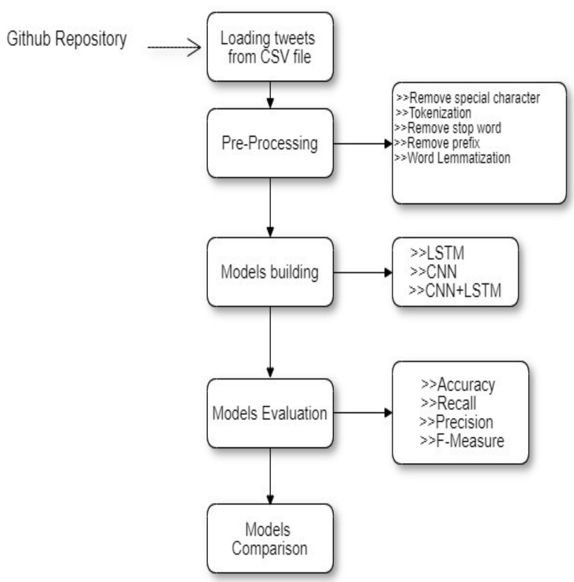

Figure 3 Research Methodology

3.1 Dataset Collection

The dataset that was used in this study is the one available in the Github repository published by Samuel K. Akpatsa on 19/03/2021 [36]. The dataset used contains 13,190 tweets about Covid-19 vaccines in English categorized into positive and negative, compiled through the Twitter API and Python script during the time period from 21/01/2021 to 10/02/2021.

3.2 Data cleaning and pre-processing

The data pre-processing stage is one of the most important stages because the quality of the data affects the results of the model. Data were cleaned and processed before feeding them to the neural networks for training. Data pre-processing includes Tokenization, Lemmatization, Stop word Removal, etc.

3.2.1 Tokenization

Tokenization is the process of dividing a sentence into single words, symbols, or tokens. Word_tokenize from the python NLTK library was used to split each tweet into tokens. The output of this stage is a list of tokens that were used as inputs to other stages of processing.

3.2.2 Lemmatization

Word Lemmatization is a process that is used to reduce each word into their common base or root. Also, Lemmatization is available through the Python with NLTK Library.

3.2.3 Stop-word removal

Stop-word is a set of commonly used words in any language. In English language examples of stop words are 'the', 'is', 'are', … etc. Stop-word removal is a cleaning process that removes most redundant and meaningless words from the text. In this study we used a stop word list for the English language that is available in python from NLTK library.

3.2.4 prefix Removal

Prefix removal is process used to remove the prefix from the sentences. Examples of prefixes are 'de-', 'dis-', 'il-', … etc.

3.3 Models Building

In this stage we built three different models: the first one is CNN, the second model is LSTM and the last one is a combination of CNN and LSTM.

3.3.1 Word embedding

The inputs that the model will be trained on must be represented as a matrix of sentences. Each row of the matrix is a vector representation of a word. The embedding layer is the first layer for all models with 3 parameters: top_words, embedding_vector_length and input_length; such that top_words is the maximum number of words for entry, embedding_vector_length is the size of vector used to present each entry and input_length is the maximum length for each entry.

3.3.2 Building and setting the CNN model

A deep CNN model using Python was built with two convolutional layers, two pooling layers and a flatten layer. The previous layers were connected through the dense layer in order to apply the classification process. The convolutional layers are used to extract features from data and learn about input with '100' filter size and '5' kernel size, we reduce the dimension of matrix by using max pooling layer with 2 pooling to reduce complexity

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and computation. After that we used Flatten layer to convert multi-dimensional array into one-dimensional array. Finally, we used dense layer with sigmoid activation function because we classify each input into positive or negative tweet. We compile our model with 'adam'[37] optimizer and 'binary_crossentropy' loss function because we work on binary classification problem.

There are many techniques that can be applied for training, but adam's algorithm has proven its efficiency for a wide range of neural network structures. It is also recommended as an effective tool for stochastic optimization because it only requires some first-order regressions, and reduces the required storage capacity.

3.3.3 Building and setting the LSTM model

A single LSTM layer was constructed with 196 neurons that utilized the sigmoid activation function by default and used dropout to prevent overfitting in training. Then the model was connected by using the dense layer with sigmoid activation function because the input classification is either positive tweet or negative tweet. The developed model was compiled with 'adam' optimizer and 'binary_crossentropy' loss function because we work on binary classification problem

3.3.4 Building and setting the CNN-LSTM hybrid model

A hybrid model which combines CNN and LSTM networks was built using Python. The hybrid model has two convolutional layers, two pooling layers and a flatten layer, which were connected through the dense layer in order to apply the classification process. The convolutional layers are used to extract features from the data with '100' filter size and '5' kernel size. The dimension of the matrix was reduced by using max pooling layer with 2 pooling size to reduce complexity and computation. After that, LSTM layer with 100 neurons was used to learn about the input. Finally, dense layer with sigmoid activation function was used because the classification of the input was either positive tweet or negative tweet. The model was compiled with 'adam' optimizer and 'binary_crossentropy' loss function because we work on binary classification problem.

3.4 Model Evaluation

The three models' performance was evaluated based on: accuracy, precision, recall and F1 scores.

Accuracy: The ratio of correct predictions (true positive and true negative) divided by the total number of all instance examined.

Accuracy= (TP+FP)/(TP+FP+TN+FN) Eq(1)

Precision: The ratio of cases that were correctly classified as positive to all cases that were classified as positive.

Precision = TP/(TP+FP) Eq(2)

Recall: The recall represents the ratio of the cases correctly predicted as positive to the actual number of positive cases.

Recall = TP/(TP+FN) Eq(3)

F1 score: the mean value of harmonics between precision and recall.

F1 score = (2*Precision*Recall)/(Precision + Recall) Eq(4), where

True positive (TP): classifying a positive sentence as positive.

False positives (FP): classifying a negative sentence as positive.

True negative (TN): classifying a negative sentence as negative.

False negative (FN): classifying a positive sentence as negative.

4. EXPERIMENTS AND RESULTS

More than 13,000 Twitter posts were contained in the dataset. In order to analyze these tweets, the data was divided into two sets: a learning set and a testing set. The learning set contained 66.6% of the data and the remaining 33.4% was used as a testing set. The three above-mentioned methods

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(CNN, LSTM and hybrid CNN-LSTM) were applied to the data set.

Initially, the models were applied to the data with an Embedding Dimension of 64, a batch size of 128, 32 filters, a kernel size of 3, a pool size of 2, 10 epochs and with different dropout values. The accuracy was computed and the results are shown in table 1. A dropout value of 0.5 achieved good results in all models.

Table 1: The accuracy of the models with different dropout values

dropout	CNN-LSTM	CNN	LSTM
0.2	0.82	0.80	0.80
0.5	0.83	0.81	0.82
0.7	0.80	0.81	0.82

In the next set of experiments, the dropout value was assigned to 0.5 and the models were applied with different values of epochs (10,20,30). The resulted accuracy when running the three models is shown in Table 2. The best accuracy was scored at (83%) for the hybrid model, 81% for the CNN model, and 82% for the LSTM model. All the previous results were generated when the number of epochs was 10.

Table 2 The accuracy of the models with different epochs values

epochs	CNN-LSTM	CNN	LSTM
10	0.83	0.81	0.82
20	0.80	0.80	0.81
30	0.80	0.79	0.80

Running the models several times and comparing the results; it was concluded that the best results were obtained using the parameters listed in Table 3.

Table 3 shows the best parameters achieved for the models.

Embedding Dimension	64
Epoch	10
Batch Size	128
Filters	32
Kernel Size	3
Pool Size	2
Dropout	0.5

Using theses parameters, the Long Short-Term Memory networks model was tested using the testing set which was composed of 3957 tweets. Of the testing set 2754 were correctly identified as positive; while 396 tweets were wrongly classified as negative. 432 were wrongly classified as positive and 375 were correctly classified as negative. The confusion matrix results generated when testing the LSTM is shown in table 4.

Table 4 LSTM confusion matrix

	Positive	Negative
Positive	2754	396
Negative	432	375

Table 5 shows the confusion matrix for the Convolutional Neural Network model, where 2867 were correctly identified as positive; while 283 tweets were wrongly classified as negative. 564 were wrongly classified as positive and 243 were correctly classified as negative.

Table 5 CNN confusion matrix

	Positive	Negative
Positive	2867	283
Negative	564	243

Table 6 shows the confusion matrix for the CNN-LSTM hybrid model, where 2895 were correctly identified as positive; while 255 tweets were wrongly classified as negative. 509 were wrongly classified as positive and 298 were correctly classified as negative.

Table 6 CNN-LSTM confusion matrix

	Positive	Negative
Positive	2895	255
Negative	509	298

The accuracy, precision, recall, and F-measure were computed based on the above mentioned formulas. A comparison of these four measures for the three models is shown in figure 4 where the hybrid model takes the lead over the individual models. The accuracy, precision, recall and f-measure values when using the parameters listed in table 3 are shown in table 7.

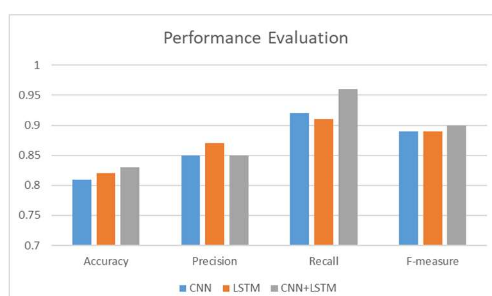

Figure 4 Comparison between the three models

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Table 7 Evaluation results of the models' performance

Model	Accuracy	Precision	Recall	F-measure
CNN	0.81	0.85	0.92	0.89
LSTM	0.82	**0.87**	0.91	0.89
CNN+LSTM	**0.83**	0.85	**0.96**	**0.90**

The experimental results showed that the performance of the hybrid CNN-LSTM model was better than the individual models, as it achieved an accuracy of 83%, while the LSTM achieved 82% and the CNN model obtained an accuracy of 81%. The Precision value was 85% for the hybrid model, the recall value was 96% and the F-measure was 90%.

5. CONCLUSION

In this paper, a hybrid model that combines CNN and LSTM deep learning algorithms was constructed. The model was applied on a data set of 13,190 tweets to analyze user sentiment towards the COVID-19 vaccine. Each sentiment is categorized into either positive or negative. The experimental evaluation of the hybrid model showed an accuracy of 83% which outperformed the accuracy of both CNN, and LSTM algorithms individually.

The research contribution is to assist the medical staff and the government in analyzing peoples' reaction toward COVID-19 vaccine. Also, it aims to provide them with a model that can assess the binary feedback of citizens, and therefore supports a better understanding of the evaluation results. Observing the results shows that the hybrid model is providing better result as compared to other techniques. Furthermore, the models show its suitability to analyze such data. Future work can be applied to combine the hybrid algorithm with another models to increase the accuracy. Moreover, different techniques can be combined and compared with the original algorithms.

REFERENCES:

[1] https://datareportal.com/social-media-users (accessed November 2021)

[2] Liu, B. (2012). Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 5(1), 1-167.

[3] Pota, M., Esposito, M., Palomino, M. A., & Masala, G. L. (2018, May). A subword-based deep learning approach for sentiment analysis of political tweets. In 2018 32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA) (pp. 651-656). IEEE.

[4] Pradhan, A., Senapati, M. R., & Sahu, P. K. (2021). Improving sentiment analysis with learning concepts from concept, patterns lexicons and negations. Ain Shams Engineering Journal.

[5] Mostafa, A., Gad, W., Abdelkader, T., & Badr, N. (2021). Pre-HLSA: Predicting home location for Twitter users based on sentimental analysis. Ain Shams Engineering Journal.

[6] Prathap, B. R., & Ramesha, K. (2018, February). Twitter sentiment for analysing different types of crimes. In 2018 International Conference on Communication, Computing and Internet of Things (IC3IoT) (pp. 483-488). IEEE.

[7] Dolianiti, F. S., Iakovakis, D., Dias, S. B., Hadjileontiadou, S., Diniz, J. A., & Hadjileontiadis, L. (2018, June). Sentiment analysis techniques and applications in education: A survey. In International Conference on Technology and Innovation in Learning, Teaching and Education (pp. 412-427). Springer, Cham.

[8] Day, Min-Yuh, and Chia-Chou Lee. "Deep learning for financial sentiment analysis on finance news providers." 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). IEEE, 2016.

[9] Rambocas, Meena, and Barney G. Pacheco. "Online sentiment analysis in marketing research: a review." Journal of Research in Interactive Marketing (2018).

[10] Chandio, Muntazar Mahdi, and Melike Sah. "Brexit Twitter Sentiment Analysis: Changing Opinions About Brexit and UK Politicians." International Conference on Information, Communication and Computing Technology. Springer, Cham, 2019.

[11] Abualigah, L., Alfar, H. E., Shehab, M., & Hussein, A. M. A. (2020). Sentiment analysis in healthcare: a brief review. Recent Advances in NLP: The Case of Arabic Language, 129-141.

[12] Nuser M, Alrashdan W, BaniBaker Q. Impact of COVID-19 Pandemic on Students' Mental Health: A Case Study of Jordanian Universities. Journal of Education and Community Health. 2022 Feb 12;8(4):229-35.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13] Thomas, Katie. "New Pfizer results: Coronavirus vaccine is safe and 95% effective." The New York Times [Internet] (2020).

[14] Knoll, Maria Deloria, and Chizoba Wonodi. "Oxford–AstraZeneca COVID-19 vaccine efficacy." The Lancet 397.10269 (2021): 72-74.

[15] Dyer, Owen. "Covid-19: Chinese vaccines may need changes to improve efficacy, admits official." bmj 373 (2021): n969.

[16] Cotfas, L. A., Delcea, C., Roxin, I., Ioanăş, C., Gherai, D. S., & Tajariol, F. (2021). The Longest Month: Analyzing COVID-19 Vaccination Opinions Dynamics from Tweets in the Month following the First Vaccine Announcement. IEEE Access, 9, 33203-33223.

[17] LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., & Jackel, L. D. (1989). Backpropagation applied to handwritten zip code recognition. Neural computation, 1(4), 541-551.

[18] Benhammou, Y., Tabik, S., Achchab, B., & Herrera, F. (2018, May). A first study exploring the performance of the state-of-the art CNN model in the problem of breast cancer. In Proceedings of the International Conference on Learning and Optimization Algorithms: Theory and Applications (pp. 1-6).

[19] Du, J., Gui, L., Xu, R., & He, Y. (2017, November). A convolutional attention model for text classification. In National CCF conference on natural language processing and Chinese computing (pp. 183-195). Springer, Cham.

[20] Dominguez-Sanchez, A., Cazorla, M., & Orts-Escolano, S. (2018). A new dataset and performance evaluation of a region-based cnn for urban object detection. Electronics, 7(11), 301.

[21] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

[22] Awan, Faraz Malik, Roberto Minerva, and Noel Crespi. "Using Noise Pollution Data for Traffic Prediction in Smart Cities: Experiments Based on LSTM Recurrent Neural Networks." IEEE Sensors Journal 21, no. 18 (2021): 20722-20729.

[23] Roondiwala, Murtaza, Harshal Patel, and Shraddha Varma. "Predicting stock prices using LSTM." International Journal of Science and Research (IJSR) 6.4 (2017): 1754-1756.

[24] Wang, Ludi, and Xiaoguang Zhou. "Detection of congestive heart failure based on LSTM-based deep network via short-term RR intervals." Sensors 19.7 (2019): 1502.

[25] Chimmula, Vinay Kumar Reddy, and Lei Zhang. "Time series forecasting of COVID-19 transmission in Canada using LSTM networks." Chaos, Solitons & Fractals 135 (2020): 109864.

[26] Ramadhani, A. M., & Goo, H. S. (2017, August). Twitter sentiment analysis using deep learning methods. In 2017 7th International annual engineering seminar (InAES) (pp. 1-4). IEEE.

[27] Dang, N. C., Moreno-García, M. N., & De la Prieta, F. (2020). Sentiment analysis based on deep learning: A comparative study. Electronics, 9(3), 483.

[28] Baktha, K., & Tripathy, B. K. (2017, April). Investigation of recurrent neural networks in the field of sentiment analysis. In 2017 International Conference on Communication and Signal Processing (ICCSP) (pp. 2047-2050). IEEE.

[29] Nguyen, Huy, and Minh-Le Nguyen. "A deep neural architecture for sentence-level sentiment classification in twitter social networking." International Conference of the Pacific Association for Computational Linguistics. Springer, Singapore, 2017.

[30] Ritonga, M., Al Ihsan, M. A., Anjar, A., & Rambe, F. H. (2021, February). Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm. In IOP Conference Series: Materials Science and Engineering (Vol. 1088, No. 1, p. 012045). IOP Publishing.

[31] Huq, M. R., Ali, A., & Rahman, A. (2017). Sentiment analysis on Twitter data using KNN and SVM. Int J Adv Comput Sci Appl, 8(6), 19-25.

[32] Wazery, Yaser Maher, Hager Saleh Mohammed, and Essam Halim Houssein. "Twitter sentiment analysis using deep neural network." 2018 14th International Computer Engineering Conference (ICENCO). IEEE, 2018.

[33] Lyu, J. C., Le Han, E., & Luli, G. K. (2021). COVID-19 vaccine–related discussion on Twitter: topic modeling and sentiment analysis. Journal of medical Internet research, 23(6), e24435.

[34] Melton, C. A., Olusanya, O. A., Ammar, N., & Shaban-Nejad, A. (2021). Public sentiment analysis and topic modeling regarding COVID-19 vaccines on the Reddit social media platform: A call to action for strengthening vaccine confidence. Journal of Infection and Public Health, 14(10), 1505-1512.

[35] Hussain, A., Tahir, A., Hussain, Z., Sheikh, Z., Gogate, M., Dashtipour, K., ... & Sheikh, A. (2021). Artificial intelligence–enabled analysis

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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.

[36] askasnr/Covid19-Vaccine-Twitter-Data. (n.d.). GitHub. Retrieved March 28, 2021, from https://github.com/askasnr/Covid19-Vaccine-Twitter-Data

[37] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.