Comparing LSTM and CNN Methods in Case Study on Public Discussion about Covid-19 in Twitter

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***Abstract*—This study compares two Deep Learning model methods, which include the Long Short-Term Memory (LSTM) method and the Convolution Neural Network (CNN) method. The aim of the comparison is to discover the performance of two different fundamental deep learning approaches which are based on convolutional theory (CNN) and deal with the vanishing gradient problem (LSTM). The purpose of this study is to compare the accuracy of the two methods using a dataset of 4169 obtained by crawling social media using the Twitter API. The Tweets data we've obtained are based on a specific hashtag keyword, namely "covid-19 pandemic". This study attempts to assess the sentiment of all tweets about the Covid-19 viral epidemic to determine whether tweets about Covid-19 contain positive or negative thoughts. Before classification, the Preprocessing and Word Embedding steps are completed, and this study has determined that the epoch used is 20 and the hidden layer is 64. Following the classification process, this study concludes that the two methods are appropriate for classifying public conversation sentences against Covid-19. According to this study, the LSTM method is superior, with an accuracy of 83.3%, a precision of 85.6%, a recall of 90.6%, and an f1-score of 88.5%. While the CNN method achieved an accuracy of 81%, precision of 71.7%, recall of 72%, and f1-score of 72%.**

***Keywords*—COVID-19; LSTM; CNN; sentiment analysis**

I. Introduction

Social media is an online platform through which the community interacts broadly and openly, and it can also be used to disseminate information. Twitter is one of the most popular social networking platforms [1]. With 18.45 million users, Indonesia ranks fifth among countries with the most active engagement on Twitter [2]. The information regarding the Covid-19 pandemic is what is being discussed now.

The Covid-19 pandemic has resulted in the implementation of all regulations and limitations in numerous nations, including Indonesia [3]. As a result, many people express their opinions about Covid-19 on social media; therefore, this discussion or community response can be classified to determine the sentiment of the statement; after determining the classification in the sentence, accuracy calculations can be produced; and the method is required so that classification is carried out structurally.

For measuring categorization accuracy, there are two methods available: Machine Learning [4] and Deep Learning [5]. There are multiple algorithms that can be applied to both models. Deep Learning is a model based on the human brain's artificial neural network; this model is an implementation of the modern Machine Learning model [6]. Deep Learning is a generic sort of learning that can handle issues in all domains, including categorization [7]; it has been defined as such. The Long Short-Term Memory (LSTM) technique [8] and the Convolution Neural Network (CNN) algorithm [9] can be employed for this categorization within this deep learning system. In the mode of deep learning with several levels (layers), the layers are the input layer, the hidden layer, and the output layer [10]. Before executing calculations using the Deep learning model of conversational sentence categorization. However, the preprocessing procedure must be executed to ensure that the input is first processed using natural language processing (NLP) [11]. NLP is a computerized technology that explains the function of software or hardware that analyzes spoken or written language in a computer system [12]. The primary objective of NLP is to have a computer system that truly understands natural language as closely as possible to humans [13]. In this study, two approaches, LSTM and CNN, will be utilized to compare the accuracy of findings.

Schmid Huber and Hoch Reiter introduced LSTM in 1997 [14]. LSTM is a method derived from the development of the Recurrent Neural Network (RNN) architecture. LSTM handles vanishing gradients by adding a memory cell that can hold information for an extended period [15].

CNN is a multilayer neural network type feed-forward network with two or more deep layers that has good performance in applications involving image data, including computer vision categorization data gathering [16] and NLP [17] with the results obtained being excellent. CNN is not significantly distinct from a typical neural network, which consists of neurons with weight, bias, and activation functions. CNN eliminates the need to do multiple steps on the neural network because it calculates the output using convolution operations on the input layer. Each layer has a distinct filter and mixes the convolution operation's results [18].

In this comparative research of the LSTM and CNN methods on the classification of community dialogues regarding Covid-19 with case studies on Twitter social media. It is intended that the conversations and reactions regarding Covid-19 conducted by the community on social media can be utilized by the Indonesian government to enhance regulations during the pandemic.

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II. Research Method

This study employed an experimental approach, which involved running several tests on the Deep Learning model with the LSTM and CNN techniques considering the following relevant studies.

A. Relevant Studies

In this relevant studies section, it was employed to assemble data pertinent to the study at hand, which will then serve as a basis for further study, comparison, and information gathering. Comparison of relevant studies can be seen in Table I. According to Table I, researchers reviewed five related publications between 2015 and 2021. In comparison to naïve bayes, support vector machines, decision trees, and random forests, the LSTM and Gated Recurrent Units (GRU) methods achieve the highest level of accuracy with a value of 99.9%. LSTM, CNN, and GRU are all neural network examples.

TABLE I. Comparison of Relevant Studies

Title	Publication Year	Method	Findings
Sentiment Analysis Twitter Bahasa Indonesia Berbasis Word2vec MenggunakanDeep Convolutional Neural Network (Sentiment Analysis Twitter Indonesian Based on Word2vec Using Deep Convolutional Neural Network)	2020 [19]	CNN	In this study, 999 Indonesian tweets were used taken from the social media Twitter. The results of experiments that have been carried out with the Deep Convolutional Neural Network algorithm acquired the highest accuracy value of 76.40%.
Penerapan Convolutional Long Short-Term Memory untuk Klasifikasi Teks BeritaBahasa Indonesia (Application of Convolutional Long Short-Term Memory for Classification of Indonesian News Texts)	2021 [20]	CNN and LSTM	This study aims to analyze the combination of two deep learning methods: CNN and LSTM (C-LSTM). The result of this combination acquired a better performance compared to CNN and LSTM.
Algoritma LSTM-CNN untuk Sentimen Klasifikasi dengan Word2vec pada Media Online (LSTM-CNN Algorithm for Sentiment Classification with Word2vec on Online Media)	2021 [21]	LSTM-CNN	Classification using LSTM, LSTM-CNN, CNN-LSTM methods with the dataset used was Indonesian article title data taken from the Detik Finance website resulting in testing the LSTM, LSTM-CNN, CNN-LSTM methods obtained accuracy results of, 62%, 65% and 74%.
Komparasi Algoritma Machine Learning Dan Deep Learning Untuk Named Entity Recognition: Studi Kasus Data Kebencanaan (Comparison of Machine Learning and Deep Learning Algorithms for Named Entity Recognition: A Case Study of Disaster Data)	2020 [22]	Naive Bayes, SupportVector Machines, Decision Tree, Danrandom Forest. LSTM, CNN, GRU.	In this study, the highest accuracy machine learning model was obtained in the random forest method with an accuracy value of 0.98%, in the Deep Learning method there were LSTM and GRU methods with an accuracy value of 0.99%.
A C-LSTM Neural Network for Text Classification	2015 [23]	LSTM, Bi LSTM, C-LSTM	The study stated that by using the combined method of CNN and LSTM to obtain a high accuracy value with an accuracy value of 94.6%

B. Experimental Design

In order to conduct research in a more systematic manner, we designed the experiment as depicted in Fig. 1. From Fig. 1 we compared the LSTM and CNN in general. In the following subsections, the specifics of Fig. 1 will be described.

- Data Crawling

Data crawling is a dataset that refers to conversation sentences originating from Twitter [24] with the hashtag "covid-19 pandemic". Data retrieval method utilizes the mining address provided by the social media platforms mentioned above. The data obtained 9,643 tweets from September 2020 to September 2022, tweet data will be used for two years during the covid-19 pandemic.

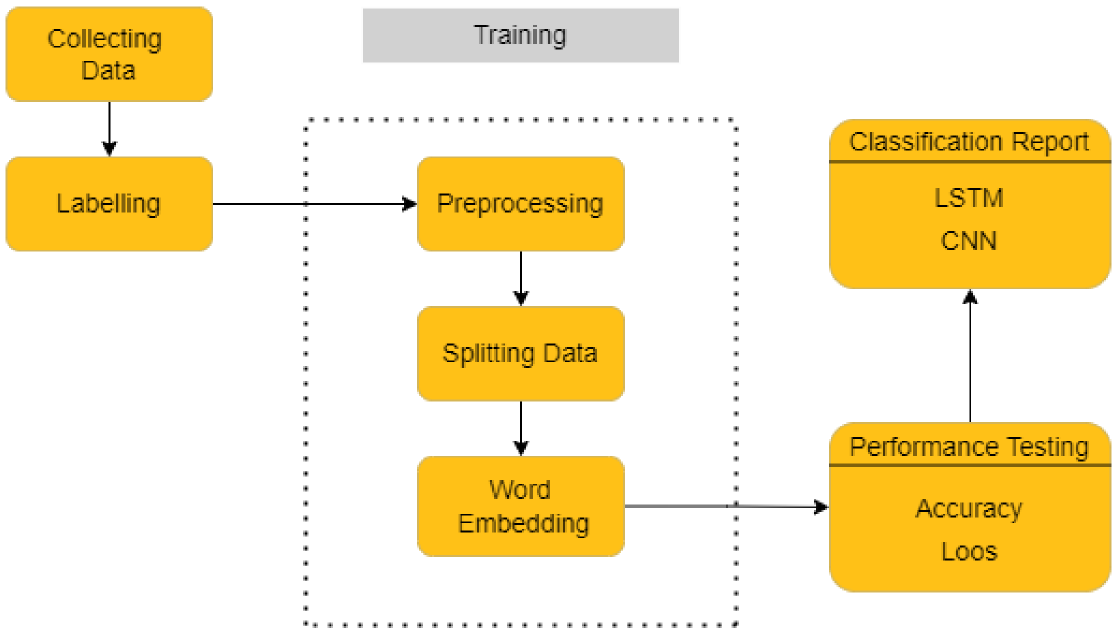


Fig. 1. Experimental Design.

- Data Labelling

In this study, data was labeled manually by language experts who already understand whether a sentence is included in a negative or positive sentence. We give a table (Table II), which contains two columns: tweet and label. The tweet column consists of the tweet status, which is collected from Twitter. The second column is an empty label. The expert should write a specific category of sentiment: negative and positive. Even though the neutral category can improve the overall accuracy, in this research we do not neutral label because it tends to be ambiguity or uncertainty. Uncertainty leads to confusion which may harm the efficiency of the decision [25]. This data labeling was done after crawling the data while the data was still intact therefore sentiment could be identified in the sentence. An example of labeled data can be found in Table II. From Table II, we obtain tweets with labels that have been validated by specialists.

TABLE II. DATA LABELLING

Tweet	Label
Kondisi ekonomi orang tua dan keluarga tengah sulit saat pandemi COVID 19, *mahasiswa Unsri tuntut keringanan UKT*. https://t.co/WwQ1pDJTrx	Negative
Jumlah kematian Covid-19 *pada Juli 2021 merupakan yang tertinggi selama pandemi.* https://t.co/Wju16vABcj	Negative
Kerjasama ekonomi Indonesia-Australia ditengah pandemi COVID-19 https://t.co/Zk3DpyiCYi	Positive
Kendati Muhammadiyah telah bekerja luar biasa melawan pandemi Covid-19 *dan diapresiasi berbagai pihak, Sekretaris U*… https://t.co/e6QlHtoKL9	Positive
Kementerian Kesehatan telah mengeluarkan Surat Edaran nomor HK.02.02/III/15242/2021 *tentang Pelaksanaan Vaksinasi C*… https://t.co/xc38o9eQgq	Positive

- Text Preprocessing

Text preprocessing is used to improve the model's efficiency and accuracy by reducing unmodeled variations [26]. The selection of appropriate pre-processing methods or a combination of pre-processing methods can affect the performance of the analysis, and improper use of pre-processing techniques can reduce the model's performance [27]. The research underwent four stages during preprocessing, which are as follows:

1) Cleaning: Cleaning is a process of removing or eliminating unnecessary words, links, characters, emoticons, and any punctuation which has no relevance to the tweets. Punctuations, for instance (!”#$%&'[]*+,-./:;<=>?@[\]^_`{|}~), and character symbols or commonly known as emoticons such as (😁😆😅⏰) must be removed. In addition, in this research, the links within the tweet such as [28] mention symbol (@), hashtag (#), retweet symbol (RT), and unnecessary space and enter were removed.

2) Case folding: Case Folding is a stage in preprocessing that functions to convert capital letters into lowercase letters.

3) Tokenizing: Tokenizing is the process of breaking a document into units of words [8]. This process is used to get a word that will be processed at the next stage.

4) Stemming: Stemming is the process of transforming the words contained in the dataset into root words. In Indonesian text, the process of removing affixes in a word. Both affixes at the beginning of words (prefixes), affixes in the middle or insertions (infixes), affixes at the end of sentences (suffixes), or combination affixes from prefixes and suffixes (confixes) were altered. The illustration of stemming preprocessing can be seen in Table III. From table III it is known that there are words that were changed before stemming and already stemming.

TABLE III. STEMMING PREPROCESSING

Tweet	Process
Kerjasama ekonomi Indonesia-Australia *ditengah pandemi* COVID-19https://t.co/Zk3DpyiCYi	Before Preprocessing
"*kerjasama*" "*ekonomi*" "*indonesia*" "australia" "*tengah*" "*pandemi*" "covid"	After Preprocessing

At this stage, it generates a ready-to-use dataset is 2,835 tweets as depicted by the graph in Fig. 2. From Fig. 2 the dataset contains 1,892 tweets of positive sentiment and 943 tweets of negative sentiment.

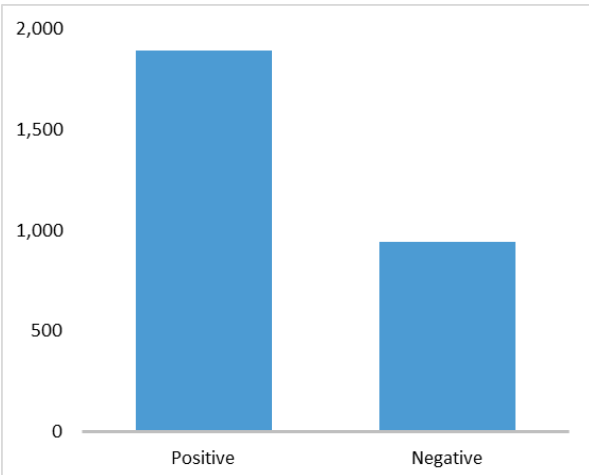


Fig. 2. Dataset Graphic.

- Data Splitting

Splitting data is a type of data sharing that occurs after the data has been processed. Data will split into two or more subsets. Data separation generally divides data into two portions, the first of which is used for test data and the second for training the model. This research divides the data into 80% of the training data and 20% of the testing data.

- Word Embedding

Word embedding is a method of creating a modified vector of word representation types that allows words with similar meanings to have similar representations [29]. In this study, two types of word embedding are used:

1) Term Frequency-Inverse Document Frequency (TF-IDF): This TF-IDF method is an algorithm for merging two methods. Which include the concept of the frequency of occurrence of terms in a document and the inverse frequency containing the word [30]. Term Frequency (tf) provides the frequency of a word in each corpus document as in (1). Inverse Data Frequency (idf): used to calculate the weight of uncommon terms over the entire corpus of documents. A high idf score is assigned to words that appear seldom in the corpus as in (2). Combining these two (tf and idf) yields the TF-IDF score (w) for a word in a corpus document. It is the result of the subsequent in (3). Where $tf_{i,j}$ represents the number of occurrences of i in j, j represents the number of documents containing i and N represents the total number of documents.

$$tf_{i,j} = \frac{n_{i,j}}{\sum k \, n_{i,j}} \tag{1}$$

$$idf\ (w) = \ log \frac{N}{df_t} \tag{2}$$

$$w_{i,j} = tf_{i,j}\ x\ \log(\frac{N}{df_i}) \tag{3}$$

2) Embedding lsyer: The embedding layer requires that data first pass through the pre-processing stage, after which the sentence is broken down into word units. The word is then assigned a vector value or weight that is seeded with a small random number [31]. The Embedding Layer is a word embedding method used in the CNN algorithm, the results of which are then processed using the CNN model.

- Classification

1) LSTM: By entering input values derived from word weighting or TF-IDF, the LSTM method can classify draft sentences. The LSTM network structure is presented in Fig. 3 [32]. As depicted in Fig. 3, the LSTM algorithm is composed of a neural network and multiple distinct memory blocks called cells. The data gathered by the LSTM method is then stored by the cell, and memory modification is performed by a component known as a gate. In the LSTM algorithm, there are three types of gates: forgate gate, input gate, and output gate.

The initial process of the LSTM in finding the forgate gate was by multiplying the weight with the input value and adding the bias after which the sigmoid activation was carried out with (4).

$$f_1 = \sigma\,(W_f\, x_1 + U_f h_{t-1} + \ bf) \tag{4}$$

The next step was to store the value of the forgate gate and calculate the input gate and candidate cell state. The input gate and candidate cell state equations are as follows (5) and (6).

$$i_1 = \sigma(W_i\, x_1 + U_i h_{t-1} + \ b_i) \tag{5}$$

$$C'_1 = tanh(W_c\, x_1 + U_c h_{t-1} + \ b_c) \tag{6}$$

Then after that, it can compute the value of the cell gates, which was obtained by combining the values of the forgate gate and the input gate. The output gate and hidden layer values could then be obtained in (7) to (9).

$$C_1 = (f_1 * C_{t-1} + \ i_1 * C'_1) \tag{7}$$

$$o_1 = \sigma(W_o\, x_1 + U_o h_{t-1} + \ b_o) \tag{8}$$

$$h_1 = o_1 * tanh\ (C_1) \tag{9}$$

In this research, the parameter settings of the LSTM that was utilized included a variety of various hidden layers, specifically 2, 8, 16, 32, and 64, with each layer including a total of 50 neuronal connections. Utilizing a sigmoid activation function, a loss function of the binary crossentropy type, the optimizer adam, a batch size of 32, and an epoch of 20. The employment of a variety of different hidden layer number scenarios has the purpose of determining the influence that the number of hidden layers utilized has on the accuracy as well as the loss that occurs as a result of using those hidden layers.

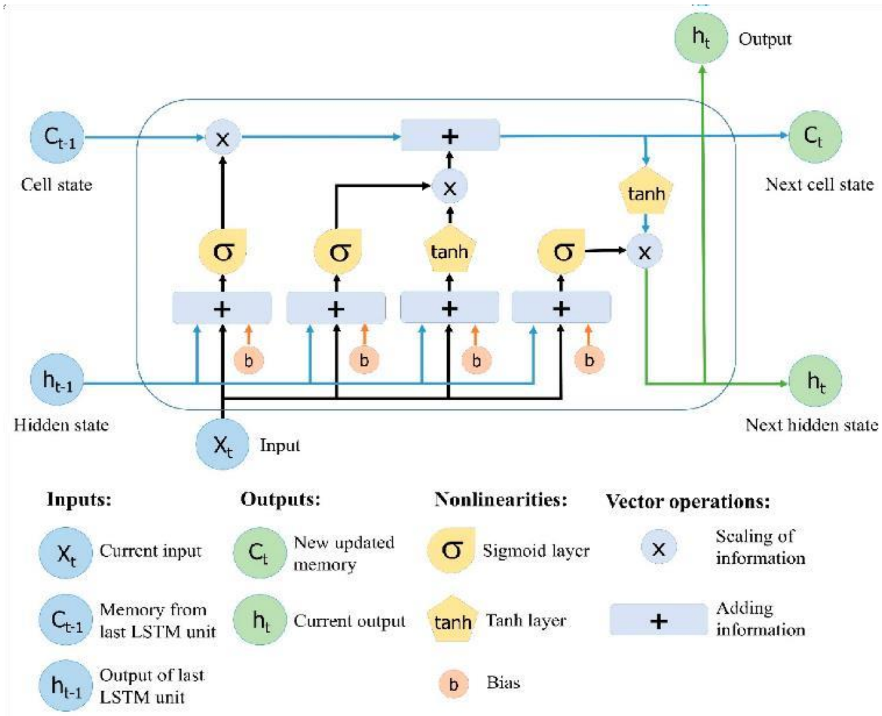


Fig. 3. LSTM Structure.

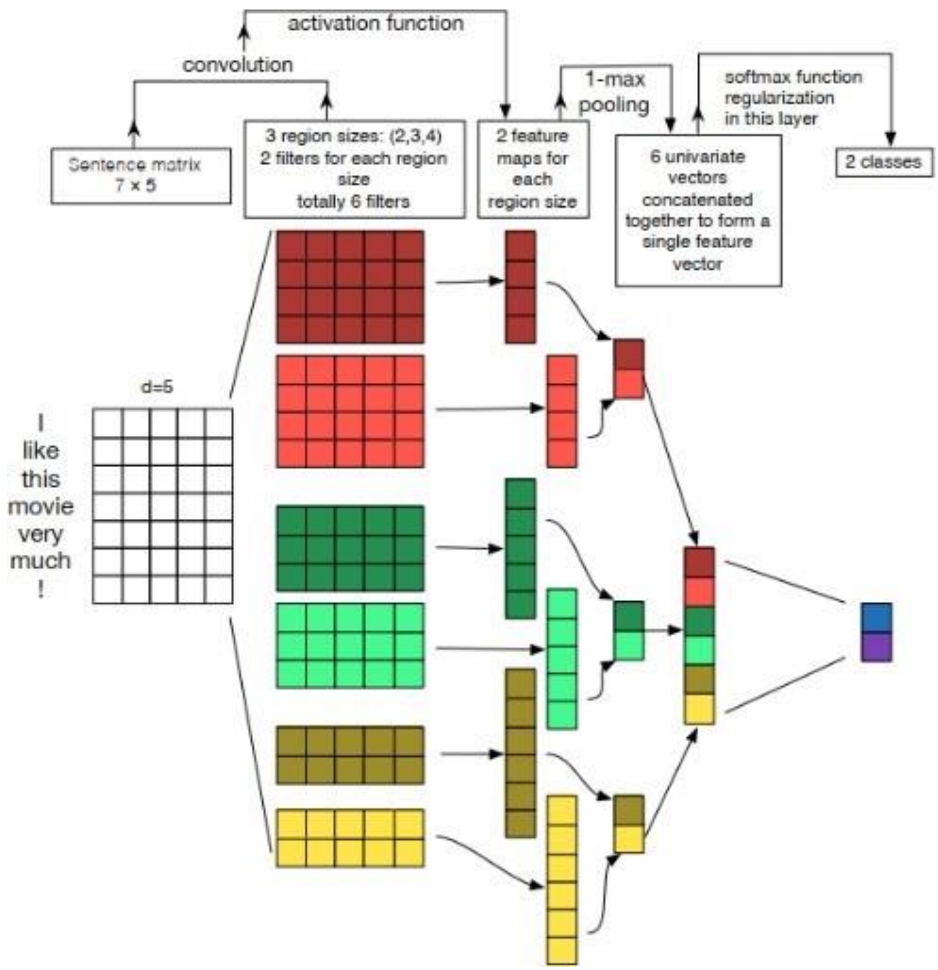


Fig. 4. CNN Model Architecture.

2) *CNN:* The input to a CNN for sentiment analysis tasks is a sentence or document represented as a matrix. The architecture of the CNN for sentiment analysis is depicted in Fig. 4 [33]. Fig. 4 describes the architecture of the CNN that will be used. This particular CNN will have one convolutional layer, and its size will be 2x2, and it will have 100 kernels. After each convolutional layer comes a maxpool layer with a size of 2 x 2, then a fully connected layer with 50 neurons in each hidden layers, and finally, a softmax layer with two neurons to represent the sentiment class comes at the end (Positive and Negative). In addition, the parameter settings used by CNN consist of the use of 20 epochs, the activation function of the Rectified Linear Unit (ReLU), the adam type optimizer, the loss function MSE, and the batch size 32. And there are scenarios using the number of hidden layers consisting of 2, 8, 16, 32, and 64.

Each row in the matrix in the Convolutional Neural Network is a token, usually a word, or it can be a character in the form of a vector that is written into a function in (10).

$$x_1{:}n = x_1 \oplus x_2 \oplus \ldots \oplus \mathrm{n} \tag{10}$$

The ⊕ operator is a concatenation operator and is used to combine words that have been converted into vectors into a matrix form followed by the activation function of the linear unit rectifier. The feature function is written in (11).

$$c_i = max(0, w\,.\,x_i{:}i + h_{-1}) \tag{11}$$

Each filter convolutes the sentence matrix $\{x_1{:}h, 2{:}h_{+1}, \ldots, 1{:}n\}$and produces feature-maps with $\epsilon\ \mathbb{R}\mathrm{n} - h_{+1}$. The feature map function is written in (12).

$$\mathrm{c} = [c_1, c_2, \ldots, c_n - h_{+1}] \tag{12}$$

Pooling on the feature map is used to continue the training process [34]. MaxPooling is the pooling method used, and it takes the maximum value of $\hat{c} = max\{\mathrm{c}\}$ as a feature based on a filter that aims to get the most important features that represent other features for each feature map. The features derived from the pooling results are employed in the classification process at the fully connected layer.

III. Results and Discussion

The implementation was carried out by comparing the Long Short-Term Memory (LSTM) and Convolution Neural Network (CNN) methods. With the hidden layer values used for experiments to determine the highest accuracy value in training and the lowest loss value in training, as well as the hidden layer value used for training. It has been determined that (2, 8, 16, 32, and 64). Both methods use an epoch value of 20 in their implementation after determining the hidden layer changes. Table IV and Table V compares the results of the accuracy and loss values in the training that was performed. Table IV shows that the LSTM method generates the highest accuracy value of 99.84% for the hidden layer value of 64 and a loss value of 0.034% for the hidden layer value of 64. The results are presented in the following Fig. 5. It differs from the CNN method, which achieves the highest level of accuracy at the hidden layer value of 64, with an accuracy value of 99.24% and a loss value of 3.95 %. In this instance, the outcome is depicted by the graph in Fig. 6.

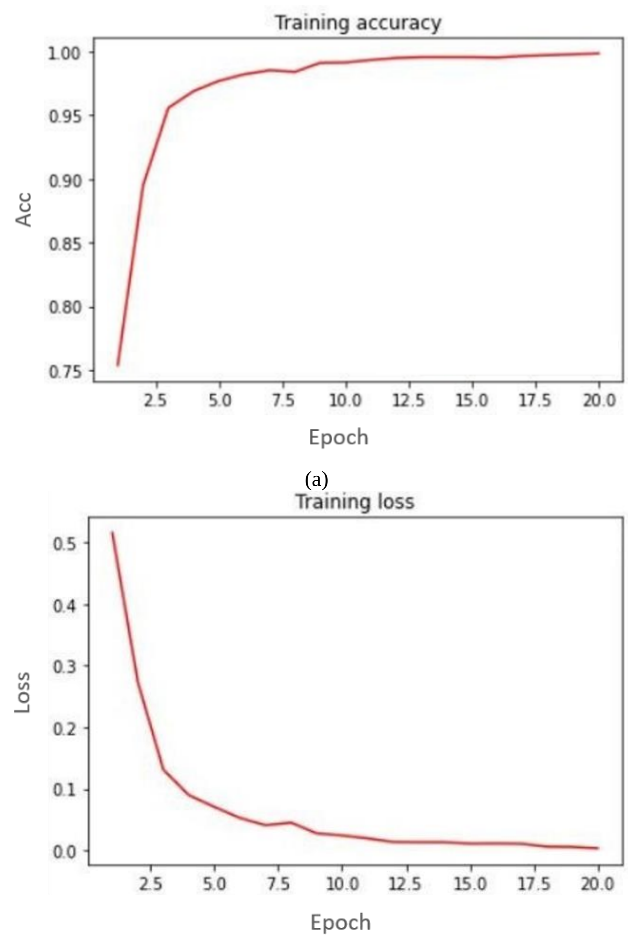
TABLE IV. Training Accuration

A Number of Hidden Layers	LSTM	CNN
2	99.68%	96.07%
8	99.74%	98.79%
16	99.69%	98.99%
32	99.71%	98.89%
64	99.84%	99.24%

TABLE V. Loss Training

A Number of Hidden Layers	LSTM	CNN
2	0.096%	13.57%
8	0.062%	5.23%
16	0.066%	2.76%
32	0.054%	5.41%
64	0.034%	3.95%

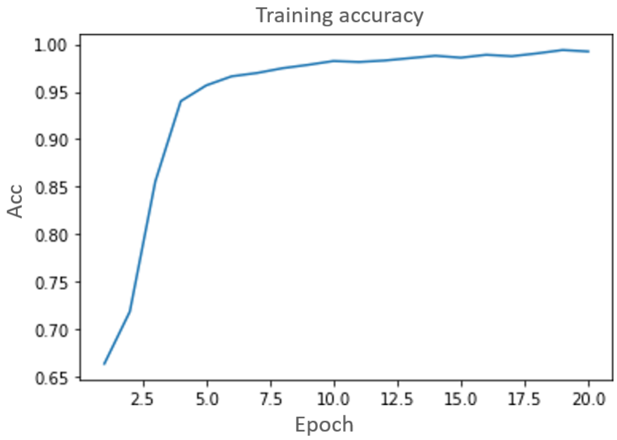
Fig. 5 is an LSTM graph illustrating the increase in training accuracy. Which indicates that the greater the epoch used, the higher the accuracy value, and if the accuracy value is high, the loss value will decrease. However, this is not always the case, the accuracy value is not always high when the epoch is high, as data and methods also influence the increase in accuracy.



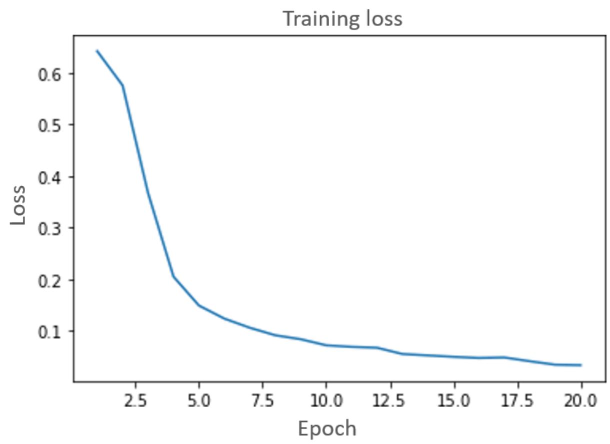
(a)

(b)

Fig. 5. LSTM Method: (a) Accuracy (b) Loss Graphs.



(a)



(b)

Fig. 6. CNN Method: (a) Accuracy (b) Loss Graphs.

Fig. 6 depicts a graph of the accuracy and loss of the CNN method which demonstrates that as the number of epochs used increases, so does the accuracy of the results. However, a large number of epochs does not guarantee that the accuracy obtained is also large; it is also affected by a number of other factors, such as the number of datasets and methods employed.

The 64th hidden layer will be used in the LSTM and CNN methods for this study. After obtaining the highest accuracy value during training and the lowest loss value during training, the researcher will use a confusion matrix to determine the final accuracy value for both methods. The following is an LSTM confusion matrix as can be seen in Table VI and CNN confusion matrix in Table VII. According to Table VI, the confusion matrix LSTM contains 504 true positive (TP) data, 145 true negative (TN) data, 78 false positive (FP) data, and 52 false negative (FN) data. CNN data from Table VII, TP 203, TN 487, FP 80, and FN 81 for confusion matrix.

TABLE VI. LSTM CONFUSION MATRIX

	Actually Positive	Actually Negative
Predicted Positvie	504	78
Predicted Negative	52	145

TABLE VII. CNN CONFUSION MATRIX

	Actually Positive	Actually Negative
Predicted Positvie	203	80
Predicted Negative	81	487

After obtaining the table confusion matrix with both methods, the performance values accuracy, precision, recall, and f1-score are reported in Table VIII. It is clear from Table VIII that both LSTM and CNN have good evaluation ratings, which means that they can be utilized for the classification of conversation sentences on Twitter relating to the Covid-19 Pandemic. The accuracy achieved by LSTM is the highest, coming up at 83.30%, whereas CNN only achieves 81.00%. Therefore, one can conclude from this research that the performance of LSTM is superior to that of CNN when it comes to analyzing people's feelings towards the COVID-19 pandemic.

TABLE VIII. VALUES ACCURACY, PRECISION, RECALL AND F1-SCORE

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM	83.30%	86.50%	90.64%	88.50%
CNN	81.00%	71.73%	71.47%	72.00%

IV. CONCLUSION

A comparison of research that has been done using datasets from social media as many as 2,835 and distribution of data by 80% of training data and 20% of testing data states that the hidden layer and epoch determine the accuracy value, with a hidden layer of 64 and an epoch of 20, the highest training accuracy value is 99.84% and the loss value is 0.034% in the LSTM met. After calculating the accuracy and loss values in training, the LSTM method achieves an accuracy value of 83.30%, precision of 86.50%, recall of 90.64%, and f1-score of 88.50% while the CNN method achieved an accuracy of 81.00%, precision of 71.73%, recall of 71.47%, and f1-score of 72.00%. This states that the LSTM method outperforms CNN in terms of performance measurement, and that both methods can be used to classify conversation sentences about the Covid-19 Pandemic on Twitter.

Many aspects were left for future investigation due to time and computational process. It would be interesting to study the following topic: a) determining whether Twitter is a more dependable source of information than Facebook, WeChat, and Instagram. Nonetheless, it is of the utmost importance to investigate other social media platforms in terms of sentiment analysis to compare. b) This research application is useful for the Coronavirus health issue and can also be adopted as a model for identifying sentiment emotion in future cases of a similar nature.

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