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Identification of Social Media Posts Containing Self-reported COVID-19 Symptoms using Triple Word Embeddings and Long Short-Term Memory

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ABSTRACT

The COVID-19 pandemic has permeated the global sphere and influenced nearly all nations and regions. Common symptoms of this pandemic include fever, cough, fatigue, and loss of sense of smell. The impact of COVID-19 on public health and the economy has made it a significant global concern. It has caused economic contraction in Indonesia, particularly in face-to-face interaction and mobility sectors, such as transportation, warehousing, construction, and food and beverages. Since the pandemic began, Twitter users have shared symptoms in their tweets. However, they couldn't confirm their concerns due to testing limitations, reporting delays, and pre-registration requirements in healthcare. The classification of text from Twitter data about COVID-19 topics has predominantly focused on sentiment analysis regarding the pandemic or vaccination. Research on identifying COVID-19 symptoms through social media messages is limited in the literature. The main objective of this study is to identify symptoms using word embedding techniques and the LSTM algorithm. Various techniques such as Word2Vec, GloVe, FastText, and a composite approach are used. LSTM is used for classification, improving upon the RNN technique. Evaluation criteria include accuracy, precision, and recall. The model with an input dimension of 147x100 achieves the highest accuracy at 89%. This study aims to find the best LSTM model for detecting COVID-19 symptoms in social media tweets. It evaluates LSTM models with different word embedding techniques and input dimensions, providing insights into the optimal text-based method for COVID-19 detection through social media texts.

INTRODUCTION

COVID-19, caused by the coronavirus, has inflicted widespread damage on global public health, the economy, and social stability (Ophinni et al., 2020). According to the World Health Organization (WHO), this grouping of diseases surpassed China's boundaries, resulting in many fatalities, ultimately prompting its categorization as a pandemic on March 11, 2020 (Fadlyana et al., 2021). In early July 2021, Indonesia confirmed 61,140 deaths attributed to COVID-19 (Jioe et al., 2022). According to the World Health Organization (WHO), Indonesia reported 161,879 deaths as of January 2024, with a reduction in the number of daily confirmed cases by 89.42% and a decrease in active cases by 44.16%, it is observed that the proportion of recovered cases stands at 97.47%, surpassing the average worldwide rate of 96%. Conversely, the mortality rate of 2.38% exceeds the corresponding global statistic of 1% (Novarisa, Helda, & Mulyadi, 2023). Common indicators suggestive of a potential COVID-19 infection encompass pyrexia (98%), thoracic exhalation (76%), and heightened weariness or discomfort (44%) (Huang et al., 2020). In order to control the rapid spread of COVID-19, governments worldwide implemented strict measures, including the quarantine of millions of people. Despite the challenges, it remains difficult to distinguish among COVID-19 patients based on their symptoms, leading to limitations in these efforts. Some individuals have reported symptoms they believe are related to COVID-19 in various settings, including social media. However, they have been unable to confirm their concerns due to limited access to testing, reporting delays, and healthcare systems that typically require pre-registration (Mackey et al., 2020).

Twitter is a widely recognized social media platform that facilitates the exchange of messages through tweets, resulting in a substantial volume of data related to public and global issues (Chintalapudi, Battineni, & Amenta, 2021). The increase in society's dependence on social media as an information source, rather than traditional news outlets, combined with the large amount of data being produced, has intensified the focus on utilizing natural language processing (NLP) and artificial intelligence (A.I.) methods to improve text analysis. (Naseem, Razzak, Khushi, Eklund, & Kim, 2021). Studies focusing on the analysis of Twitter data related to the pandemic, using Support Vector Machine (SVM) and word embeddings like TF-IDF and FastText, achieved an accuracy of 88.72% (Didi, Walha, & Wali, 2022). Research (Klein et al., 2021) utilizing Bidirectional Encoder Representations from Transformers (BERT) on English-language tweets with location data related to potential COVID-19 cases obtained an F1-Score value of 76%. A study (Cai, Li, Nali, & Mackey, 2021) gathered COVID-19 symptom-related tweets from the public Twitter Application Programming Interface (API) using XLNet, achieving an accuracy of 91%. Research by (Mengistie & Kumar, 2021) concerning sentiment analysis classification related to COVID-19 using Convolutional Neural Network and Bidirectional Long Short-Term Memory (CNN-Bi-LSTM) with FastText resulted in an accuracy of 99.33%, while GloVe achieved an accuracy of 97.55%. Other studies related to NLP with text datasets have also been conducted, such as research on understanding disease behavior and its relation to mortality cases (Mackey et al., 2020), (Wan et al., 2020), analysis of catastrophe events (Parimala et al., 2021), and the classification of reviews for microblogs that include emojis (Li et al., 2023).

Previous research (Suhaili, Salim, & Jambli, 2022), (Kumar Singh, Sharma, & Paul, 2020), (Karim, Chakravarthi, McCrae, & Cochez, 2020) has tended to use a single feature extraction method combined with classification algorithms like LSTM. Text classification from Twitter data related to COVID-19 topics has primarily focused on sentiment analysis concerning the COVID-19 pandemic or COVID-19 vaccination. However, research on detecting COVID-19 symptoms from Twitter social media messages using a combination of word embedding feature extraction methods has been relatively limited in Indonesia. This study aims to investigate the effectiveness of the LSTM model in detecting COVID-19 symptoms from tweets on the Twitter social media platform. The model employed in this study is an LSTM model with feature extraction using Word2Vec, FastText, GloVe, and a combination of all three-word embeddings merged using the concatenate method, resulting in an input size of 147x100. We conduct an assessment that includes measuring accuracy, precision, and recall to assess the model's effectiveness. This study examines the efficacy of not only amalgamating multiple approaches but also appraises other facets, specifically the efficacy of the parameters employed in said approaches. As mentioned earlier, the approaches and parameters used in this study are the most commonly utilized in NLP models to generate the optimal model. This comprehensive evaluation lets us pinpoint the model demonstrating the most exceptional performance. Additionally, we analyze how different feature extraction methods and input sizes impact the performance of each model, ultimately seeking to ascertain the most suitable model for the particular focus of this research.

The main accomplishment of this study resides in identifying the LSTM model that exhibits the utmost exceptional efficacy in detecting COVID-19 by analyzing tweets on social media. While prior research has delved into sentiment analysis classification and various feature extraction methods employed in NLP, this investigation breaks new ground. By examining the efficiency of LSTM models with various feature extraction combinations, this research provides fresh perspectives on the most effective text-based approach for early COVID-19 detection. This particular investigation holds significant value as it serves as a crucial foundation in selecting the most suitable LSTM methodology that can be utilized for the early identification and detection of the COVID-19 virus.

RESEARCH METHODS

The primary objective of this investigation is to ascertain the optimal strategy for identifying COVID-19 in its initial phase by utilizing social media. The LSTM algorithm will be implemented for classification purposes in this inquiry. Consequently, the word embedding techniques employed comprise Word2Vec, GloVe, and FastText and a fusion of all three word embedding methodologies. Different word padding inputs are utilized for each experiment, consisting of the maximum length of a word in a sentence (max_length), mean, median, and mode. The LSTM model is then evaluated using accuracy, precision, and recall. The procedure in this research can be seen in Figure 1.

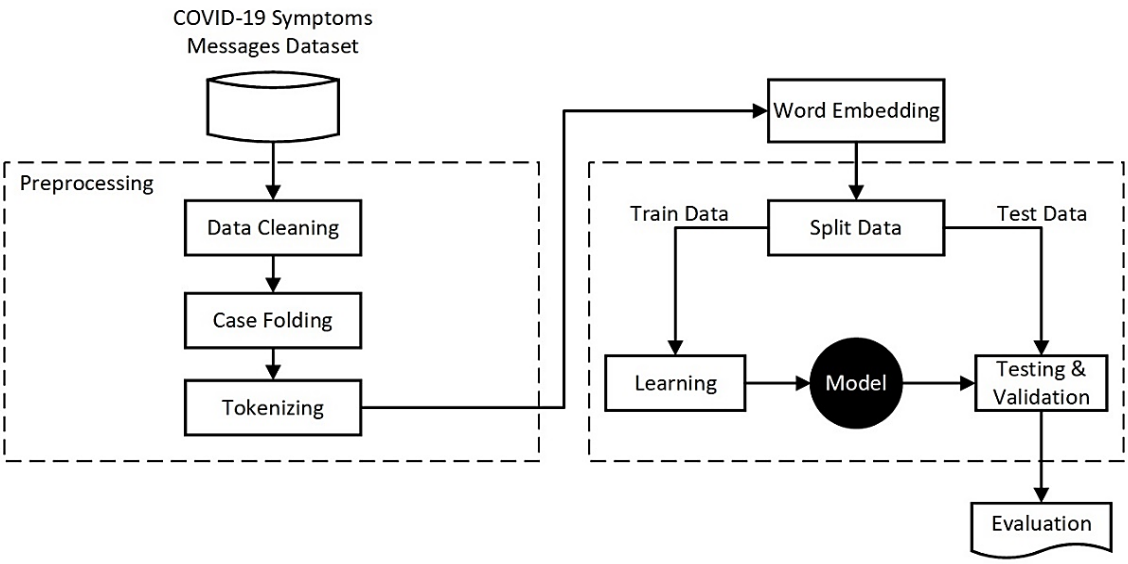


Figure 1. Research Procedure

1. Data Collection

The dataset employed in this study for training and testing data pertained to COVID-19 symptom tweets sourced from the social media platform Twitter (Khairie et al., 2023). The dataset can be downloaded at https://github.com/rezafaisal/RisetCovid/tree/main/data/teks. To obtain this dataset, Twitter tweets that incorporated keywords associated with COVID-19 symptoms were gathered, and subsequently, researchers manually organized and categorized the collected tweets.

There are 1000 data points, comprising 500 tweets from individuals with confirmed COVID-19 symptoms and 500 tweets from individuals not indicating COVID-19 but experiencing the same symptoms. Table 1. represents a sample of the data labeled as positive and negative.

Table 1**.** COVID-19 Symptoms Dataset

No	*Text*	*Label*
1	Qadarullah pak suami negatif NS-1 positif covid, plus ku jg sama positif covid. Suami cm bergejala 3 hari di awal (demam 40 derajat) skrg pilek ma batuk2. Ku baru ada gejala kemarin, demam 38 drjt, pusing ma linu2 badan	Positive
2	tapii pas kena covid kmrin keulang lg. apalgi di hari 1-5. sesek nafas, buat ngomg aj susah bgt dah kek di ujung maut karna selain sesak nafas jg demam, pusing, batuk. dah cukup y covid ajg u dah pernah nyiksa w.	Positive
…	…	…
500	Ga enak badan, kepala pusing.. Bukan gegara covid, krna ga punya uang aja	Negative
501	Gw tenggokan gatel, terus swab tuh besoknya karena kontak dg org positif 5 hari sebelumnya. Alhamdulillah hasilnya negatif.	Negative

2. Preprocessing Data

This stage transforms the raw tweet data into more structured data. This study's stages are cleaning (Faisal et al., 2022), converting uppercase letters to lowercase (HaCohen-Kerner, Miller, & Yigal, 2020), and tokenization. Data cleaning involves removing unwanted characters and specific Twitter-related words from the text data, such as hyperlinks, double spaces, tweet-specific syntax (@, #), and non-alphanumeric characters. Case folding is standardizing the letter case to lowercase since computers distinguish between uppercase and lowercase, and converting them to lowercase ensures uniformity in data dimensions. Tokenization involves segmenting and converting the text into a list of integer tokens (Omuya, Okeyo, & Kimwele, 2023).

After the completion of the preprocessing stage for the entirety of the textual data, the subsequent step involves enumerating the quantity of words present in each text message. Following this, the maximum length, mean, mode, and median values are derived from the statistical analysis of the word count. Consequently, a process known as word padding is implemented in order to ensure the uniformity of the word count across all messages within the given text data set (Faisal et al., 2022). Different word padding lengths can impact model performance and yield varying results for each padding type (Lopez-del Rio, Martin, Perera-Lluna, & Saidi, 2020). Smaller input padding reduces memory usage, whereas larger padding consumes more memory. Afterwards, the dataset is divided into two sets: the training data, which accounts for 80% of the dataset, and the testing data, which accounts for the remaining 20%. A random split is employed to ensure an unbiased allocation. The distribution of the number of words used in this study is presented in Table 2.

Table 2. Number of Words Value

Dataset	*Word Padding*	*Num. of Words*
COVID-19 Symptoms Dataset	Max	49
	Mean	15
	Median	13
	Mode	5

3. Long Short-Term Memory (LSTM)

The preprocessed COVID-19 symptom dataset from social media, with defined padding lengths, was then subjected to processing using an LSTM. LSTM has been widely utilized in text data classification research and offers the advantage of handling larger datasets (Kim & Pyun, 2020). The

LSTM models employed in this study encompass LSTM with three popular word embedding techniques. Using three-word embedding models, various data structures are formed with varying dimensions. The integration of structured data derived from the output of feature extraction techniques compensates for the limitations of a particular technique through the implementation of alternative techniques (Faisal et al., 2022). All models underwent training with the parameters as specified in the list in Table 3.

Table 3**.** Dataset Description

Parameter	*Value*
Batch size	32
Epoch	150
Neuron	256
Optimizer	Adam

LSTM was developed to address the vanishing gradients problem in RNN (Sherstinsky, 2020). LSTM can remove or add information to the data based on the existing training by employing three main gates (Zhao, Mao, & Chen, 2019): an input gate to transmit information from a sigmoid layer to determine which information should be added. Then, this new information is combined with the next layer for processing. An output gate serves as the final gate to produce information from the data, which can act as the ultimate gate for a piece of information or a part of the first stage before the information is further processed through the input gate in the next cell.

Lastly, a forget gate permits the transmission of output information with significant weights from the preceding neuron. The content contained within the forget gate is retained within the memory system contingent upon the outcomes of heightened activation. If the input unit experiences heightened activation, the information is preserved within the memory cell. Conversely, input information with substantial weights is stored within the memory cell. The internal configuration of the LSTM is visually depicted in Figure 2.

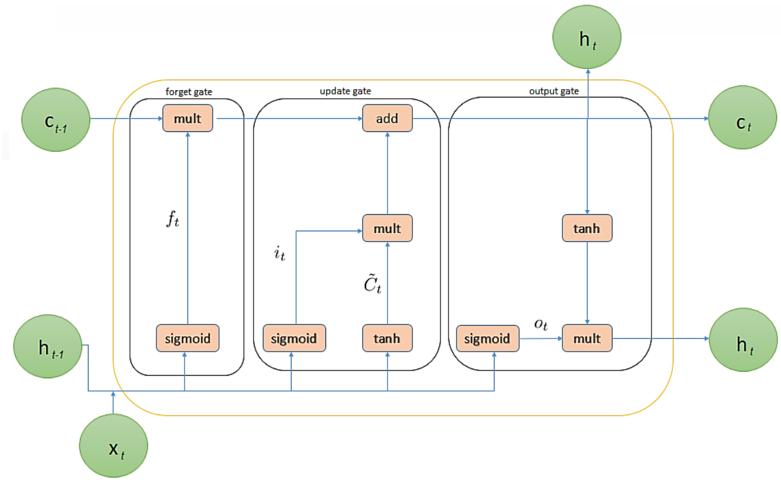


Figure 2. LSTM Architecture

4. Confusion Matrix

This study employs accuracy, precision, and recall as evaluation metrics. The confusion matrix contains classification information about the actual data and the predictions made by the classification model. The information values generated from the confusion matrix include true positive (T.P.), true negative (T.N.), false positive (F.P.), and false negative (F.N.). Higher accuracy values indicate better overall model performance. The (Firlia, Faisal, Kartini, Nugroho, & Abadi, 2021), (Nafiz, Kartini, Faisal, Indriani, & Hamonangan, 2023). The formula for accuracy can be seen in (1).

$$Accuracy = \frac{TP + TN}{Total} \quad (1)$$

Recall measures the proportion of accurately classified true instances out of the total number of instances in the true positive and negative classes, and it is employed to assess the accuracy of the classification model of actual instances (Kattenborn, Leitloff, Schiefer, & Hinz, 2021), with the recall formula provided in (2).

$$Recall = \frac{TP}{FN+TP} \quad (2)$$

Precision is a measurement that indicates the proportion of accurate instances correctly classified as true among all positive predictions (Ghorbanzadeh et al., 2019). It determines the genuineness of the classified areas in relation to COVID-19. The formula for precision is available in (3).

$$Precision = \frac{TP}{FP+TP} \quad (3)$$

RESULTS AND DISCUSSION

1. Results

In this study, the Python programming language is utilized to implement LSTM. The Keras library, which offers a highly efficient and accessible interface for addressing various challenges in machine learning, is employed. Keras encapsulates the entire process of machine learning, ranging from data preprocessing to parameter tuning and deployment. The dataset is divided into 80% training data and 20% testing data for the purpose of model classification. Four different models were utilized, each employing distinct techniques for feature extraction, such as Word2Vec, FastText, GloVe, and a combination thereof. The default input configurations include maximum, mean, median, and mode text lengths. As used in this research, the architecture of LSTM with a single word embedding feature extraction is displayed in Figure 3. Further explanation of this architecture can be found in Table 4.

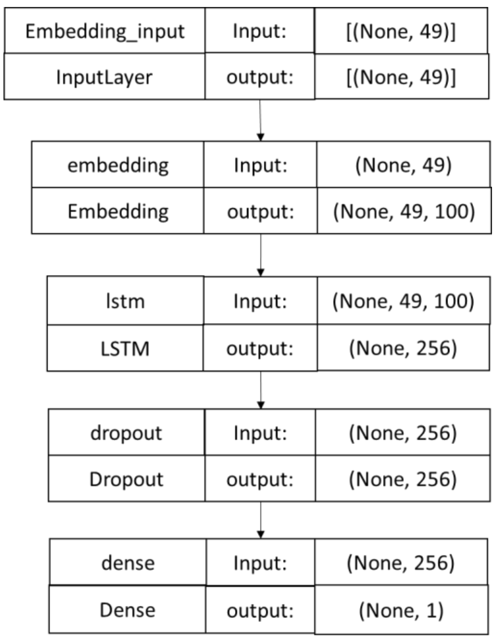


Figure 3. LSTM with one feature extraction architecture

Table 4. LSTM Architecture's Layers, Shapes, and Params

Layer (type)	*Output Shape*	*Param #*
Embedding (Embedding)	(None, 49, 100)	292600
lstm (LSTM)	(None, 256)	365568
dropout (Dropout)	(None, 256)	0
dense (Dense)	(None, 1)	257
Total params: 658, 425		
Trainable params: 365, 825		
Non-trainable params: 292,600		

The model is then tested using the testing data. The results of the LSTM experiments with different word embeddings (Word2Vec, GloVe, and FastText) can be observed in Table 5, Table 6, and Table 7.

Table 5. Experimental Results of the LSTM Model with Word2Vec

Model	*Padding Length*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*
LSTM + Word2Vec	Max	87	84	91
	Mean	78.5	77	82
	Median	77.5	76	80
	Mode	68	71	61

Table 6. Experimental Results of the LSTM Model with GloVe

Model	*Padding Length*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*
LSTM + GloVe	Max	84.5	87	81
	Mean	81.5	85	76
	Median	75	78	69
	Mode	61.5	61	64

Table 7. Experimental Results of the LSTM Model with FastText

Model	*Padding Length*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*
LSTM + FastText	Max	86	86	86
	Mean	75	76	73
	Median	79.5	79	80
	Mode	69	69	68

The architecture of LSTM with a combination of the three word embeddings, Word2Vec, GloVe, and FastText, can be seen in Figure 4, and an explanation of the architecture is provided in Table 8, the results obtained using the LSTM method with combined word embeddings can be observed in Table 9.

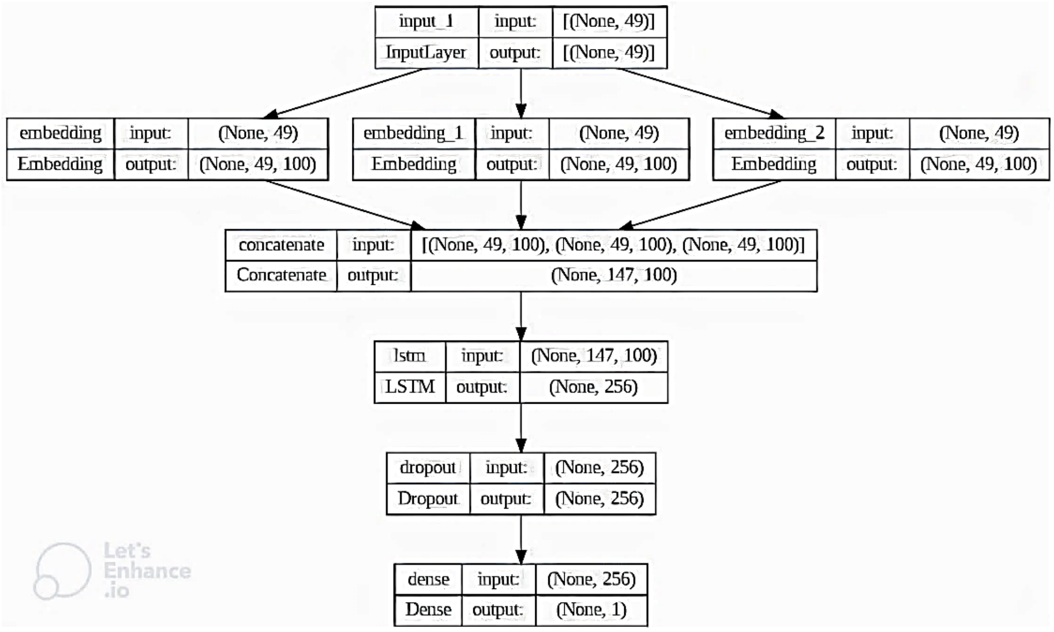


Figure 4. LSTM with combination feature extraction architecture

Table 8. LSTM Architecture's Layers, Shapes, and Params

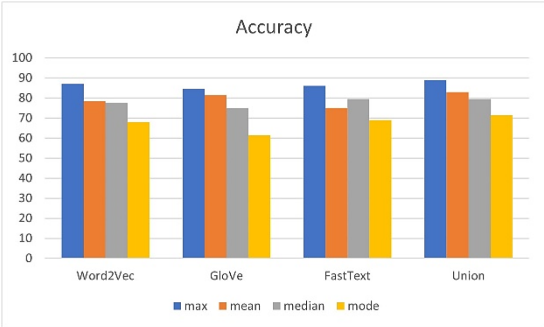
Layer (type)	*Output Shape*	*Param #*
Input_1 (InputLayer)	[(None, 49)]	0
Embedding (Embedding)	(None, 49, 100)	292600
Embedding_1 (Embedding)	(None, 49, 100)	292600
Embedding_2 (Embedding)	(None, 49, 100)	292600
Concatenate (Concatenate)	(None, 147, 100)	0
Lstm (LSTM)	(None, 256)	365568
Dropout (Dropout)	(None, 256)	0
Dense (Dense)	(None, 1)	257
Total params: 1,243, 625		
Trainable params: 365, 825		
Non-trainable params: 877,800		

Table 9. Experimental Results of the LSTM Model with Combined Feature Extraction

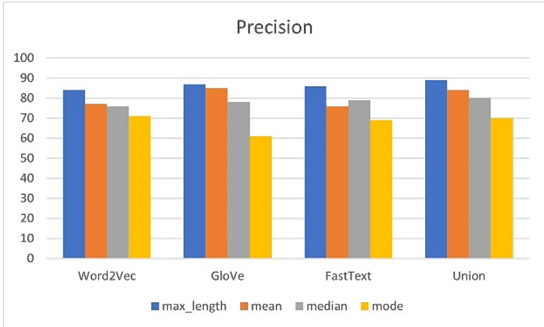
Model	*Padding Length*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*
LSTM + Word2Vec, Glove, FastText	Max	89	89	89
	Mean	83	84	82
	Median	79.5	80	79
	Mode	71.5	70	75

2. Discussion

As evident in the comparison of results between Table 5., Table 6., and Table 7, the highest accuracy and precision are achieved with the LSTM method using a padding length of Max. It can be observed that using word padding with a Max value consistently yields better results than using mean, median, or mode values. Revisiting the data in Table 9 indicates that the number of words produced by Max is larger than with other padding lengths, which provides more information in the data compared to other values. Furthermore, from the comparison, it can also be seen that the combination of Word2Vec, GloVe, and FastText word embeddings performs the best in terms of accuracy and precision. As known, each word embedding has its own strengths, and when their data is combined, each technique complements the others. As a result, combining structured data with the combination of the three word embeddings yields an accuracy of around 89%, which is better than if the three word embeddings were used standalone. The performance comparison results for accuracy, precision, and recall values can be observed in Figure 5.



a



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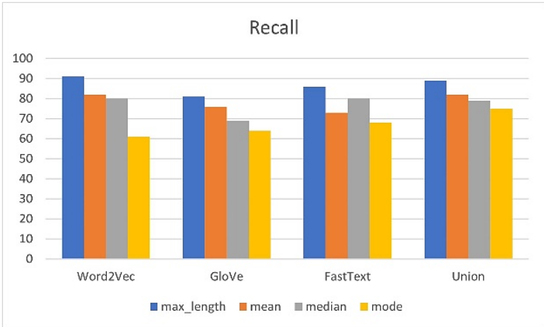

c

Figure 5. Performance charts of each models (a) Accuracy, (b) Precision, (c) Recall

The accuracy results of each tested model were then used to calculate the average values for each feature extraction method. The obtained results indicate that, on average, the Word2Vec method yielded a score of 77.75%, the FastText method had an average score of 77.38%, the GloVe method had an average score of 75.63%, and the average score for the combination of all three methods was 80.75. These results demonstrate that the combined method achieved the highest score compared to the standalone methods. Each word embedding method has its own strengths, and by combining them, all three word embeddings collaborate to create strong overall performance. The comparison chart can be seen in Figure 6.

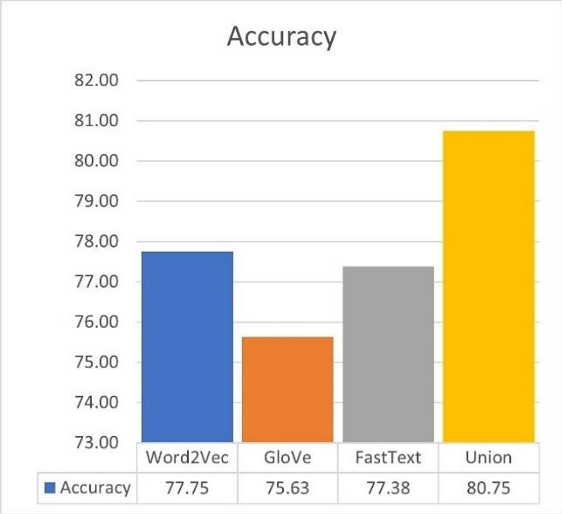

Figure 6. Comparison of Average Accuracy based on Feature Extraction Techniques

The accuracy results corresponding to the padding lengths were also used to calculate the average values for comparison purposes. The results indeed show that the input value of padding length has an impact on the model's performance and yields different results for each padding type. The padding lengths used were the maximum value, mean value, median value, and mode value, which can be reviewed in Table 2. The comparison chart can be seen in Figure 7.

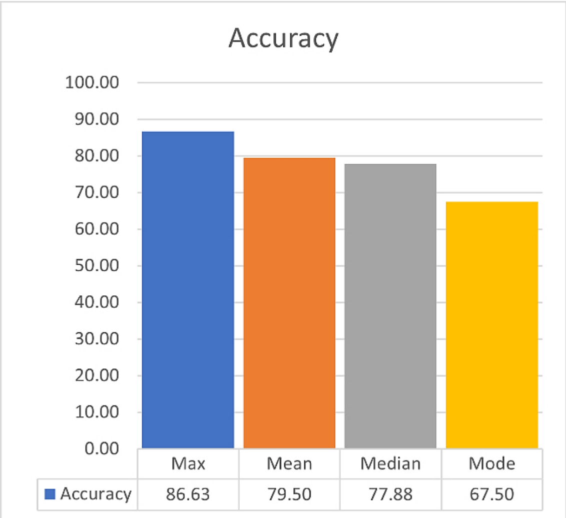

Figure 7. Comparison of Average Accuracy based on Word Padding Technique in Sentences

CONCLUSIONS AND RECOMMENDATIONS

This study explores the impact of different input sizes of padding length on the performance of the LSTM model in detecting COVID-19 symptoms through messages from the Twitter social media platform. The research also compares feature extraction methods to determine the most suitable one for text data, as in this study, and employs a combined method using three feature extractions (Word2Vec, GloVe, FastText). After conducting various experimental scenarios, it was determined that the most appropriate padding length for COVID-19 symptom tweet data is in accordance with the maximum text length present in the dataset, which is 49 words with average accuracy score 86.63%. The best-performing model involves combining several feature extractions, which in this study include a combination of three word embedding feature extractions, with the highest accuracy achieved using a padding length with a maximum number of words, amounting to 89%.

In future research, classification can be further improved by using methods aimed at achieving higher accuracy results. In the subsequent research, the researchers will explore parameter tuning experiments using grid search hyperparameter tuning and experiment with various other classification algorithms suitable for text mining, such as Bidirectional Encoder Representations from Transformer (BERT).

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