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Evaluations of Emotion Analysis of Tweets using Bidirectional Long Short Term Memory and Conventional Machine Learning

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Abstract - Many ideas are contained in the social media twitter as a form of expression for an event. This review can be used to determine a person's emotions based on text data so that we can determine the next action in addressing and responding to that opinion. Emotion classification on twitter can be done by recognizing the tweet text pattern of the user. In this study, representing emotions using the BiLSTM model and the Conventional Machine Learning model. The amount of learning rate and the number of layers and the optimizer used and the number of epochs in the BiLSTM model can affect the accuracy results. In the conventional machine learning model, the K value of the KNN, the selection of the naive bayes model on probabilistic, and the Decision Tree variation in the values of Max-depth, min-leaves, min-split will affect the results of the accuracy value. So that we get a good model for the classification of emotional sentiments based on text data from an opinion on the tweets page.

Keywords *- Tweet; Emotion; BiLSTM; Machine Learning*

I. INTRODUCTION

Emotional detection of texts on social media is a research area that has a high interest, especially those with an interest in emotional analysis [1]. One of them is the Twitter social media which is widely used to express someone's ideas or opinions about many things about an event [2]. Emotional classification on twitter can be done by using the pattern recognition method in the text of twitter user reviews. This message is popularly known as a tweet. A Tweet is a short message with a length of characters limited to 140 characters [3]. In this study, we used text-only data from Twitter users to determine these emotions.

Models built for emotional representation based on text mining can use machine learning algorithms or deep learning algorithms. The deep learning algorithm that we use is BiLSTM (bidirectional long short-term memory) because the BiLSTM model will learn all special words and ordinary words, and pay attention to the relationship or dependence between words [4]. This model can fully get contextual information, and get the important parts of the sentences in the training itself in a simple and effective manner [5]. Likewise in conventional machine learning we use the K-Nearest Neighbors (KNN) algorithm, Decision Tree and Probabilistic models. We tested how deep learning models and machine learning parameters affect the classification process.

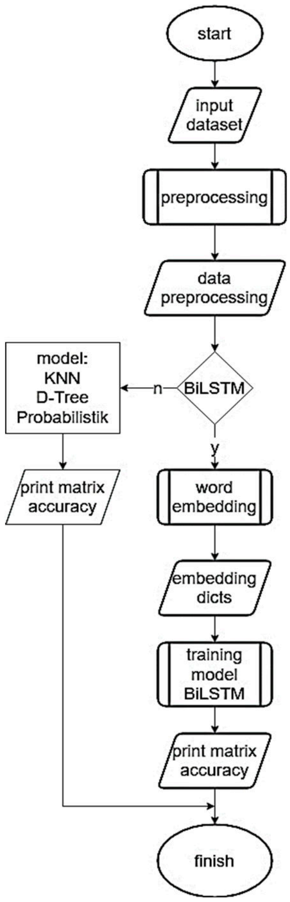

Figure 1.
Research Outline

In previous research regarding the classification of emotions based on tweet pages using the machine learning support vector machine (SVM) algorithm, naïve Bayes classifier, multilayer perceptron (MLP) and clustering gave strong predictive accuracy results with 95.9%. However, this can be said to be good because it only applies to one method of the model, because by not varying the hyperparameter or the parameter values so that the result can be said to be more dominant to the dataset [6].

Twitter data is also used in emotional analysis research during the COVID-19 pandemic, using the NCR Lexicon method with the classes anger, anticipation, disgust, fear, joy, sadness, surprise, and trust, with the resulting accuracy of 80%. This method considers from a word or a group of words to deduce feelings. The Lexicon approach can describe a keyword-based approach. Emotion detection on keywords is matched with predefined emotional

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keywords. because the Lexicon method only considers predetermined emotional keywords based on the labels of these emotions, the results obtained will depend on the labels that have been defined. Therefore, in this study we used the BiLSTM method which will consider the words before and after to predict emotions [7].

Likewise, research conducted using tweet text data to predict positive or negative sentiment related to the 2019 Indonesian Presidential Election using the conventional machine learning Support Vector Machine (SVM), Multinomial Naive Bayes (MNB), and Logistic Regression (LR) methods with TF-IDF weighting and without TF-IDF. Five Deep Learning algorithms are also used, such as Convolutional Neural Network (CNN), CNN-LSTM, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU)-LSTM, and Bidirectional LSTM with batch sizes of 128 and 5 epochs. The best accuracy of 84.60% is achieved on the Bidirectional LSTM. BiLSTM is built using the embedding layer as input with three arguments, namely input, and output dimensions, and input length. then dropout layer, 2 BiLSTM layers with 256 hidden nodes, then dropout layer, dense layer, and output layer [8].

Our contribution in this paper is that we do a thorough comparison on the method of variation optimizer Bidirectional LSTM with Adam, Nadam, RMSprop, and SGD, variation is hidden layer 1 through 3, and a variety of learning rate of 0.1, 0.01, and 0001. In conventional machine learning, we add a KNN model with variations in neighbor values 1, 3, 5, 7, 9, 11, 13, 15, 17, 19. The Decision Tree model uses entropy criteria and the Gini index on pruning max_depth, min_samples_leaf, and min_samples_split with 6 value variations. The Naive Bayes Gaussian, Complement, Bernoulli, Multinomial, and Logistic Regression algorithms are used in the probabilistic model.

The purpose of this research is to find a good model for sentiment classification of emotions based on text data of an opinion on a tweets page. This opinion is interesting to classify which can characterize a person's mental state, because knowing a person's emotions when writing a tweet on twitter will be able to help find out good or bad reviews or feedback from users, so that by knowing these emotional tendencies, it can be used as a reference. to determine the next action in addressing and responding to opinions and ideas.

II. Research Method

A. Dataset

Text tweet and emotional data used is a public dataset, namely the Twitter Reviews for Emotion Analysis dataset which is taken from the Kaggle link [9]. The dataset consists of four columns including Sl no, Tweets, Search key and Feeling. Sl no is an ordered number from the contents of the data, Tweets contain text reviews from Twitter users, search key keywords used, and Feeling are emotions classified using keywords containing six emotions, namely Angry, Disgust, Fear, Happy, Sad and Surprise. This dataset is created using the twitter API by implementing keywords.

The dataset has 10017 reviews which will be input text and emotions as output labels. For each classification model to be built, we divide the data into 80% training data and 20% test data with a random state value of 1. So that 8013 training data and 2004 test data are generated. Training data will be used to input data from the model being built and test data will be used for data input as a classification analysis and the accuracy of the model being built.

B. Preprocessing

Preprocessing is a process of processing unorganized forms of data into data that is better than noise so that it is ready to be used in building classification models in text mining [10]. A review of the Tweets dataset column in this study will first carry out the preprocessing process, then the data from the preprocessing results will be used to build a classification model.

There are several steps carried out in this preprocessing, namely checking the data dimensions, data type and checking whether there are empty data or not. Delete unused columns, namely Sl no and Search key. Perform LabelEncoder for Y data (Felling) as labels. Case folding of X data (Tweets) as input data. Then the X data is tokenized by replacing contractions, tabs, new line and back slice. Remove non ASCII. Removes mentions, links, hashtags and removes incomplete URLs. Removing punctuation, number, leading and trailing white space, multiple white space into single white space, deleting single character and after that, tokenize. Then the last preprocessing step is filtering stop words and filtering lemmatize verbs.

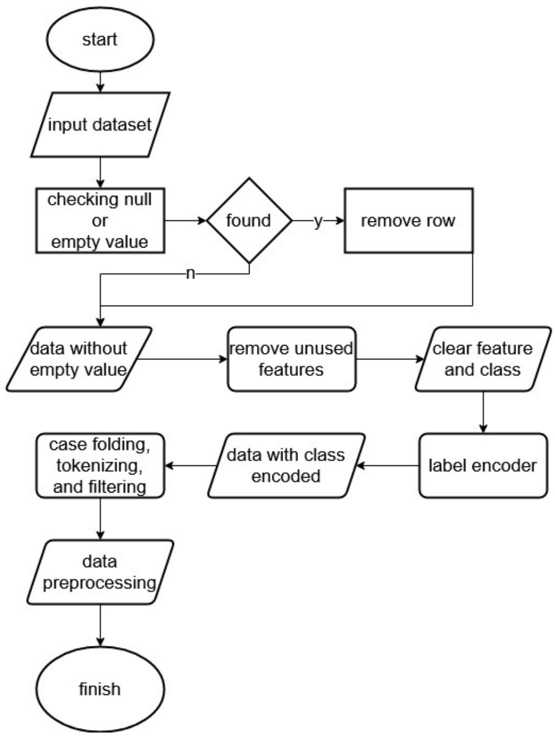

Figure 2. Preprocessing

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C. Word Embedding

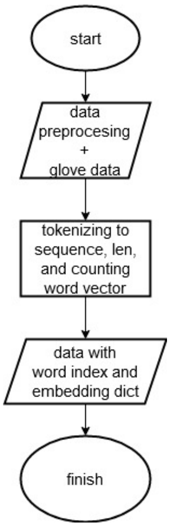

Figure 3. Word Embedding

Word embeddings are often used in Natural Language Processing (NLP) to build deep learning models, especially in BiLSTM because vector representations generated from words will capture semantic properties that can be useful and relate linguistically between words [11]. In this study, we used the extraction feature with the embedding layer glove.twitter.27B for the value to the word input and the word vector, namely the 50d glove. glove embedding will result in a statistically trained word vector space on the global word, which will result in a better model than word2vec in the case of NLP (analogy) [12].

D. Bidirectional Long-Short Term Memory

Bidirectional Long Short Term Memory is a neural network of Long Short Term Memory (LSTM) which consists of two layers of LSTM neural network [10]. Bidirectional LSTM connects two hidden layers from opposite directions to the same output. With this generative form of deep learning, the neuron layer can be obtained information from the past and future conditions simultaneously [13]. The two layers of the LSTM neural network are called the forward and backward LSTM. The combination will capture information from both directions [14]. Bidirectional LSTM can improve model accuracy [15].

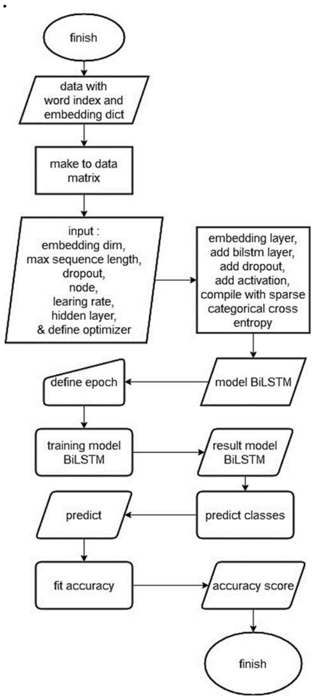

Figure 4. BiLSTM

In this study, the BiLSTM Architecture model that was built has several layers including the embedding layer, dropout layer, BiLSTM layer and output layer. To calculate the loss model, use the sparse categorical cross-entropy function. The BiLSTM model we built uses deep learning hard. BiLSTM was varied using four optimizers, namely Adam, Nadam, SGD and RMSprop. For each optimizer use lstm_node = 31. Then for each optimizer varied with hidden layer 1, hidden layer 2, and hidden layer 3. Then in each hidden layer using variations of the learning rate 0.1, 0.01 and 0.001. each model uses relu activation and output uses softmax activation. While the parameters tested for performance in this study are epoch with an epoch value of 20, then the parameters for learning rate and dropout. To evaluate the model as a benchmark we use an accuracy matrix to measure the predictive quality of the model built.

Model Building Architecture
Model Sequential
21707 Unique Tokens (10017,500)
Total 1193514

Table 1. Architecture BiLSTM Hiden Layer 1

Optimizer: Adam, Nadam, SGD, RMSProp
Hidden Layer: 1

learning Rate	lstm_node	epoch	dropout
0.1 0.01 0.001	31	20	0.5

layer (type)	output shape	param	activation function
Embendding	(None, 500, 50)	1085400	Relu
Bidirectional	(None, 500, 64)	21248	Relu
Dropout	(None, 500, 64)	0	Relu
Bidirectional_1	(None, 64)	24832	Relu
Dropout_1	(None, 64)	0	Relu
Dense	(None, 256)	16640	Relu
Dense_1	(None, 6)	1542	Softmax

Total params: 1.149.662
Trainable params: 1.149.662
Non-trainable params: 0

Table 2. Architecture BiLSTM Hiden Layer 2

Optimizer: Adam, Nadam, SGD, RMSProp
Hidden Layer: 2

learning Rate	lstm_node	epoch	dropout
0.1 0.01 0.001	31	20	0.5

layer (type)	output shape	param	activation function
Embendding	(None, 500, 50)	1085400	Relu
Bidirectional	(None, 500, 64)	21248	Relu
Dropout	(None, 500, 64)	0	Relu
Bidirectional_1	(None, 500, 64)	24832	Relu
Dropout_1	(None, 500, 64)	0	Relu
Bidirectional_2	(None, 64)	24832	Relu

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Dropout_2	(None, 64)	0	Relu
Dense	(None, 256)	16640	Relu
Dense_1	(None, 6)	1542	Softmax
Total params: 1.174.494			
Trainable params: 1.174.494			
Non-trainable params: 0			

Table 3. Architecture BiLSTM Hiden Layer 3

Optimizer: Adam, Nadam, SGD, RMSProp
Hidden Layer: 3

learning Rate	lstm_node	epoch	dropout
0.1 0.01 0.001	31	20	0.5
layer (type)	**output shape**	**param**	**activation function**
Embendding	(None, 500, 50)	1085400	Relu
Bidirectional	(None, 500, 64)	21248	Relu
Dropout	(None, 500, 64)	0	Relu
Bidirectional_1	(None, 500, 64)	24832	Relu
Dropout_1	(None, 500, 64)	0	Relu
Bidirectional_2	(None, 500, 64)	24832	Relu
Dropout_2	(None, 500, 64)	0	Relu
Bidirectional_3	(None, 64)	24832	Relu
Dropout_3	(None, 64)	0	Relu
Dense	(None, 256)	16640	Relu
Dense_1	(None, 6)	1542	Softmax
Total params: 1.199,326			
Trainable params: 1.199,326			
Non-trainable params: 0			

E. Conventional Machine Learning

Conventional Machine Learning already has a very mature system and many, problem solving methods are easy enough for today's computers, this method can only handle one-dimensional data [16]. Because conventional machine learning is a learning system using the training data set as a trained model of machine learning, this pre-trained model will be used to recognize the set from the test data, then from the training data it can classify from the test data set. Conventional Machine Learning focuses on statistics, data analysis and processing [17]. Conventional machine learning algorithms include Support Vector Machine (SVM), Discriminative Analysis, Naïve Bayes Classifier, Decision Tree, K-means clustering, Principal Component Analysis (PCA) and K-Nearest Neighbors (KNN) [18].

In this study, only three models of conventional machine learning algorithms that we built are the K-Nearest Neighbors (KNN) algorithm, Decision Tree and Probabilistic models using preprocessed datasets, then for each model we determine the X data from feature Tweets and data. y as the label of Feature Felling. Matrix to measure the quality of the model's prediction using the accuracy matrix.

In the KNN model for X data a CountVectorizer is performed, normalizing the data using the MinMaxScaler. Then build the KNN model by varying the neighbors value, namely 1, 3, 5, 7, 9, 11, 13, 15, 17, 19. In the Decision Tree model, make a CountVectorizer for X data then build the model using the entropy criteria matrix and the Gini index. For each of the criteria using prepruning max_depth with a variation of values, namely 5, 10, 15, 20, 25, and 30. Prepruning min_samples_leaf with a variation of values, namely 2, 5, 8, 11, 14, and 17. As well as prepruning min_samples_split with Variations in values are 4, 6, 8, 10, 11, and 14. In the Probabilistic model a CountVectorizer is performed first for X data, then normalizes the data using MinMaxScaler. The model built on the probabilistic classifier uses naïve Bayes Gaussian, Multinomial, Complement and Bernoulli. As well as building a probabilistic Logistic Regression model with max_iter = 1000.

III. Results and Discussion

Table 4. Accuracy Results of the BiLSTM Model

Optimizer	Learning Rate	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3
Adam	0.1	41.77%	41.77%	41.77%
	0.01	86.68%	87.17%	82.03%
	0.001	85.23%	85.88%	85.88%
Nadam	0.1	47.85%	13.22%	41.77%
	0.01	87.82%	87.57%	84.38%
	0.001	85.43%	84.63%	85.48%
RMSProp	0.1	27.19%	41.77%	41.77%
	0.01	87.17%	86.43%	86.03%
	0.001	81.24%	85.23%	85.78%
SGD	0.1	41.77%	41.77%	41.77%
	0.01	85.68%	82.88%	67.56%
	0.001	86.53%	84.23%	83.18%

Based on Table 1 above, the results of the accuracy metric to measure the quality of predictions generated the highest accuracy of 87.82% on the Nadam optimizer, learning rate 0.01, and hidden layer 1. These results occur because the Nadam optimizer performs a stochastic gradient descent based on first-order and second-order adaptive moment estimates. by momentum extension which involves calculating the moving average is down from the projected gradient position in the search space rather than the actual position itself. And supported by the number of datasets that we use is not too much and the selection of the right learning rate, because the learning rate is an effective way to improve training, the definition of an incorrect learning rate can lead to poor local solutions where the value of the loss function will be worse than another local solution, in the method used the main parameter that has the biggest effect on

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performance is the learning rate [19]. So the optimizer and learning rate has a great effect on the learning process in the neural network [20].

Table 5. Accuracy Results of the KNN Model

K (n_neighbors)	Accuracy (%)
1	73.55%
3	76.00%
5	76.80%
7	78.29%
9	77.84%
11	76.95%
13	75.50%
15	75.10%
17	74.00%
19	73.60%

Based on Table 2 above, the results of the accuracy metric to measure the quality of predictions resulted in the highest accuracy of 78.29% in the KNN model with a value of K = 7 which indicates that the dataset we use in this study has identical word proximity but because of multi labels so the results depend on the order proximity of training data. These results are different from studies that have been conducted to classify the objectivity of online news using KNN whose accuracy continues to increase in the variation of neighbor values 1,3,5,7 and 9 [21].

Table 6. Accuracy Results of the Decision Tree Model

Prepruning	Variation Value	Entropy (%)	Gini Index (%)
max-depth	5	57.04%	57.53%
	10	61.48%	61.08%
	15	63.67%	64.12%
	20	66.57%	67.32%
	25	69.76%	70.16%
	30	72.16%	72.21%
min-leaves	2	85.58%	86.13%
	5	85.68%	86.23%
	8	85.38%	86.33%
	11	84.93%	86.43%
	14	84.73%	85.73%
	17	85.28%	85.28%
min-split	4	87.03%	86.43%
	6	86.78%	86.58%
	8	86.53%	86.53%
	10	86.23%	86.23%
	12	85.63%	85.53%
	14	85.43%	85.43%

Based on Table 6 above, the results of the Decision Tree Model accuracy metric to measure the quality of the prediction resulted in the highest accuracy of 87.03% in the Min Split 4 Entropy criteria. This means that the data we use has great heterogeneity, and the application of pruning on min-split 4 is able to reduce data noise better than other pruning, so that if the more complex internal nodes are separated, it will result in a decreased accuracy value. This result is different from the studies that have been conducted to predict sentiment related to movie reviews using Maximum Entropy only give in 60.67% which indicates that the vector quality chosen for film review data has low performance compared to other classifiers [22].

Table 7. Accuracy Results of the Probabilistic Model

Model Naïve Bayes	Accuracy
Gaussian	48.90%
Multinomial	81.14%
Complement	82.78%
Bernoulli	82.24%
Logistic Regression	86.93%

Based on Table 7 above, the results of the accuracy metrics for the Probabilistic Naïve Bayes Model and logistic regression to measure the quality of predictions resulted in the highest accuracy of 86.93% in the Logistic Regression. These results are different from studies that have been carried out to classify a person's personality with a dataset crawled on Twitter media to students taking the 2013 Telkom University psychological test. The model was built using Logistic Regression with TF-IDF weighting at a ratio of 90:10, resulting in the best accuracy of only 33.5 % [23].

IV. CONCLUSION

Model good for sentiment classification of emotions in this study is the BiLSTM model with the optimization of Nadam, Hidden Layer 1, and 0.01 Learning Rate using epoch 20 with an accuracy of 87.82%. The amount of learning rate and the number of layers and optimizers used and the number of epochs in the BiLSTM model can affect the accuracy results.

Good preprocessing on the dataset is needed to get the ideal data and eliminate problems that interfere with the time and results of data processing because better data will produce better text mining models.

For research in the future, it is expected to do the training models with variations better tunning with the results of better performance, so the accuracy in predicting emotions on Twitter would be more accurate.

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