

Classification of Final Project Titles Using Bidirectional Long Short Term Memory at the Faculty of Engineering Nurul Jadid University

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Abstract— Every year, the Faculty of Engineering at Nurul Jadid University forms a committee to manage the process of students' final projects from the title selection stage to the final examination process until graduation. The process of selecting the final project title is still done manually, namely by checking the titles one by one, which takes a long time and allows errors because there is a lot of data to check, so human errors can also occur. Therefore, this research proposes to use the Bidirectional Long Short Term Memory (BiLSTM) method to classify the final project title based on its grade category. Several experiments were conducted to generate the most appropriate labels. The first experiment produced 4 labels and the second experiment produced 2 labels. From the results of several experiments, it was concluded that the second experiment had the best accuracy results with the 'good enough' and 'good' classes. The oversampling technique was then applied to overcome overlapping data, and the turning process was then performed on several parameters that could re-optimize the previous accuracy result of 75.24% to 91.15%. With a configuration of 10 random state parameters, using 64 batch sizes and 50 epochs. In addition, model adjustments were made to the hidden layer by adding a dropout layer and relu activation.

Keywords— Final project, Classification text, BiLSTM, Hyperparameter turning.

I. INTRODUCTION

As a requirement for graduation at a college or university, students must complete a final project[1] therefore have an impact on future academic endeavours or jobs that require a higher level of knowledge[2]. Therefore, dissertations are often created to assess a student's ability to apply their knowledge and skills. The final project involves research on a problem within a specific research topic, guided by a supervisor, and by following some related guidelines. The final project involves researching a problem on a specific topic with the guidance of a supervisor and following some related guidelines[3].

The process of completing the final project is not an easy process and requires full commitment in going through several stages, such as submitting the final project title, proposal seminar, preparing the final project report, and final project trial[4]. Therefore, every stage in completing the final project

must be undertaken wholeheartedly and with high commitment.

Submitting the final project title is the first step in completing the final project. Determining the right title is very important because the title must meet the standards set, such as the product produced, the theory used, novelty, and a clear object. A title that does not meet the standards can hinder the next process in completing the final project.

To select the final project title and some interests for the final project, the Faculty of Engineering of Nurul Jadid University formed a selection team committee that is responsible for selecting the final project title. However, the selection process for the final project title is currently still done manually by the selection team. This takes a long time in the selection process and risks producing human error. Human error can be caused by a lack of seriousness, physical problems or mental fatigue in completing work, or even rushing to complete work[5].

Therefore, a manual approach to text categorisation is impractical due to high workload and low efficiency[6]. A new innovation is needed to assist the selection team in selecting final project titles efficiently. One technique that can help the selection team in selecting final project titles efficiently is to create a model for text classification. As explained in[7], the application of text classification allows almost anything to be organized, arranged, and categorized based on its class. Text classification, which typically involves assigning labels to documents based on their content, is a challenge in text mining. This can involve single label problems (one text to one label) or multiple label problems (one text to many labels)[8].

The current research proposes a text classification method using machine learning natural language processing (NLP) to address these issues. Because it allows the system to operate more freely, the use of categorisation using Natural Language Processing (NLP) is increasingly being developed. As can be seen above, the use of NLP is considered to be more efficient than the use of conventional techniques. There are various approaches to Natural Language Processing (NLP), including [9]that using the LSTM method to classify the sentiment of online coronavirus discussion topics, Classification of COVID-19 related tweets in Nepal using a set of CNN's[10].

This research will use the latest development algorithm of neural networks, namely Bidirectional Long Short-Term Memory (BiLSTM) in making the final project title classification model because from research [11] has shown that the Bi-LSTM method is one of the most successful methods in the context of text classification by comparing the use of Bi-LSTM in sentiment analysis with neural network (RNN), convolutional neural network (CNN), traditional LSTM, and Naïve Bayes (NB) methods. The results show that Bi-LSTM outperforms the other methods, producing better contextual information and higher precision, recall and F1 than other methods. To achieve this goal [12] In this research, data processing will be carried out from before and after so that it can obtain more accurate data. This is done in order to understand the context of the data better and ensure the classification of the final project title based on the class is more precise [13].

There have been many previous studies on the use of text classification especially in classifying final project titles [14][15][16]. Although there have been many previous studies conducted related to classifying final project titles, these studies only classify based on the research topic and have not used the latest algorithms. This time, the researcher attempted different research by classifying the final project title based on its score using the latest method of neural networks by using several experiments in labeling.

In addition, many melting experiments were run on the data to determine which melting was best for this investigation. In the future, it is hoped that this will speed up the process of selecting project titles. The final value recorded as a reference for the grouping of final project title.

The purpose of this research is to create an efficient final project title classification model by developing the Bidirectional Long Short-Term Memory (Bi-LSTM) method with the hope of helping the selection team to classify final project titles more efficiently at the Faculty of Engineering, Nurul Jadid University.

II. METHODOLOGY

In this study, as like Fig. 1 after identifying the problem, namely in the process of selecting the final project title which is still done manually, the next step is for researchers to conduct a literature study of several scientific publications on text classification, deep learning, NLP, BiLSTM, and python.

Only then can an action be taken to achieve the goal of this research, namely to classify the final project title based on the value listed in the dataset into a "grade" label using Bidirectional LSTM. First collect the dataset of the recapitulation of the final project title grades of the previous few years through the SIAMTEK account owned by the lecturer, then dilute the data by doing several experiments.

Several labelling trials were performed on the data, the first of which was to round the values first and then label based on the rounding results. The second trial is to label based on a predefined range of values.

Furthermore, pre-processing the data by lowercasing, removing spaces, removing single characters, and removing irrelevant letters, and performing text tokenization and creating sequence data. Next, divide the pre-processed data into 80% training data and 20% testing data. We train the Bidirectional LSTM model on the training data and evaluate its performance on the testing data.

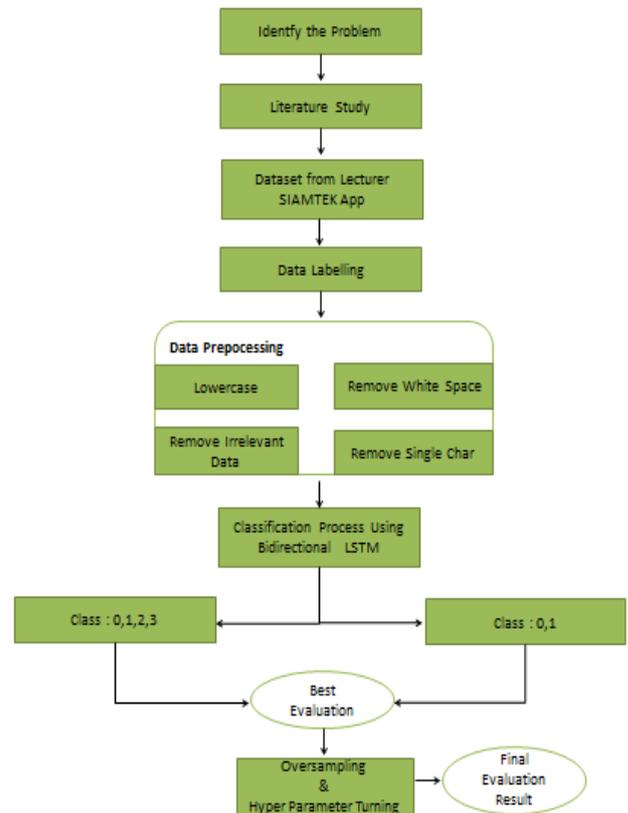


Fig. 1. Flow of Research

A. Dataset

In this study, the dataset used consists of 1149 data on titles and final assignment grades from students in the Faculty of Engineering between 2018 and 2021. The data are divided 80:20 into training and testing data. The training data, totalling 1064 data, is used to build the model, while the testing data, totalling 266 data, is used to evaluate the accuracy of the model's predictions.

Next, the data was labeled with several experiments. first, from the rounding results, poor, fair, good, and excellent classes were produced. The details of the number of each class are as Fig. 2:

```

df['grade'].value_counts()
Baik      665
Cukup    394
Sangat Baik  84
Buruk      6
    
```

Fig. 2 Details of Value in Each Class

Another experiment is to make a dilation based on the value range 67-79 being the 'Good Enough' category and the value

range 80-95 being in the 'Good' category, and to delete data that are very far from the other classes, namely the value range '50-64', so that the total data used is 1143 data with details as shown in Fig. 3.

```
df['grade'].value_counts()
cukup_baik    884
baik           339
```

Fig. 3 Details of Value in Other Experiments

In the initial process of selecting which data to use, in Fig. 4 is the initial data and the results of the data selection process in this study only 'title' and 'value' as shown in Fig. 5 are used as labels.

	judul	nilai	grade
0	Aplikasi perizinan santri di pondok pesantren ...	71	cukup_baik
1	SISTEM MONITORING KEGIATAN BADAN PEMBINAAN KHU...	80	baik
2	APLIKASI PENCATATAN KEUANGAN PADA PANTI ASUHAN...	73	cukup_baik
3	PENERAPAN PENGAJARAN NAHWU DALAM PENGAJARAN BA...	70	cukup_baik
4	Sistem Pendukung Keputusan Penilaian Kinerja K...	70	cukup_baik

Fig. 4 Data before the selection process

	judul	grade
0	Aplikasi perizinan santri di pondok pesantren ...	cukup_baik
1	SISTEM MONITORING KEGIATAN BADAN PEMBINAAN KHU...	baik
2	APLIKASI PENCATATAN KEUANGAN PADA PANTI ASUHAN...	cukup_baik
3	PENERAPAN PENGAJARAN NAHWU DALAM PENGAJARAN BA...	cukup_baik
4	Sistem Pendukung Keputusan Penilaian Kinerja K...	cukup_baik

Fig. 5 Data after the selection process

The next step is to select the data to be used in the next process and convert the target variable to a numeric as in Fig. 6 value so that the system can process it.

	judul	grade
0	aplikasi perizinan santri di pondok pesantren raudlatul fatah di desa maron berbasis web	0
1	sistem monitoring kegiatan badan pembinaan khusus (bpk) putri mts nurul jadid berbasis web dan android	1
2	aplikasi pencatatan keuangan pada panti asuhan nahdlatul ulama probolinggo berbasis web dengan menggunakan codeigniter	0
3	penerapan pengajaran nahwu dalam pengajaran bahasa arab di pondok pesantren nurul islam alhamidy berbasis android	0
4	sistem pendukung keputusan penilaian kinerja karyawan di pt tanjung windu .dengan metode fuzzy dan ahp	0

Fig. 6 Result of convert target data

B. Preprocessing Data

Text processing is used to transform the unstructured input into more structured data that can be examined with high accuracy by the model. The text processing techniques performed sequentially include data cleaning and tokenization.

During the data cleaning process, the data in the "title" column will be converted to lowercase, spaces will be removed, single characters will be removed, and unimportant letters will be removed which shown in the Fig. 7.

	judul
0	aplikasi perizinan santri di pondok pesantren raudlatul fatah di desa maron berbasis web
1	sistem monitoring kegiatan badan pembinaan khusus (bpk) putri mts nurul jadid berbasis web dan android
2	aplikasi pencatatan keuangan pada panti asuhan nahdlatul ulama probolinggo berbasis web dengan menggunakan codeigniter
3	penerapan pengajaran nahwu dalam pengajaran bahasa arab di pondok pesantren nurul islam alhamidy berbasis android
4	sistem pendukung keputusan penilaian kinerja karyawan di pt tanjung windu .dengan metode fuzzy dan ahp

Fig. 7 Sample data after preprocessing

The next stage is tokenization, which is the technique of splitting up words in a sentence with the aim of making the words form an array to facilitate analysis[17]. than step includes padding, which is used to balance the length of each sequence.

C. Bidirectional Long Short Term Memory

Then the data is divided 80:20 into training and testing data. While training data is used to build the model, testing data is used to evaluate the prediction accuracy of the model. The BI-LSTM model, which belongs to the Deep Learning model, is used in the modeling stage. Deep Learning can be used to classify text and image data. To disable inactive perceptrons and prevent overfitting[18] a dropout layer is also used.

In this stage, the architecture design of the latest development model of the neural network is carried out, which has the best chance of accuracy[19]. BiLSTM can be considered as a neural network with a programmable design, so that its shape can be adjusted to the application[20]. In addition, research[21]discusses the advantages of BiLSTM itself which is able to improve RNN which only has short-term memory and is unable to process long sequential data BiLSTM itself is a variation of the LSTM model that has two layers whose directions are opposite to each other. Fig. 8 illustrates how two LSTM, one moving forward and one moving backward, form a bidirectional long short-term memory (BiLSTM). Data can be stored in both forward and backward directions in this network[22].

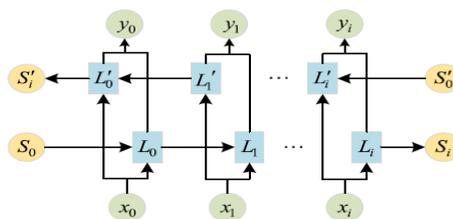


Fig. 8 The BiLSTM Structure

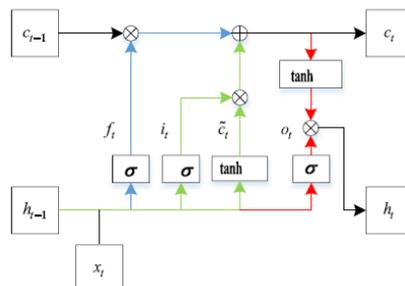


Fig. 9 LSTM's Cell Structure

As shown in Fig. 9, L and L' in Fig. 8 are the cell architecture

of the LSTM. The LSTM consists of a number of unit cells, each of which has an input gate(i_t), an output gate(o_t) and a forgetting gate(f_t).

Foot chooses whatever facts from the past to throw away. It determines which data is fed into the network and the output value is between 0-1, as shown in formula (1); it also determines which layer is used for the output, as illustrated in the formula (2); it also determines which structure is used for the output and the output value is within 0-1, as presented in formula (3); it also determines which of the current units is output to the hidden layer (h_t), as shown in formula (4); and it also determines the predicted final output (\hat{y}_t) as appears in formula (5).

$$f_t = \sigma(w_{fx} \cdot \chi_t + w_{fh} \cdot h_{t-1} + b_f) \quad (1)$$

$$i_t = \sigma(w_{ix} \cdot \chi_t + w_{ih} \cdot h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma(w_{ox} \cdot \chi_t + w_{oh} \cdot h_{t-1} + b_o) \quad (3)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (4)$$

$$\hat{y}_t = f(w_{yh} \cdot h_t + b_y) \quad (5)$$

D. Hyper Parameter Turning

The fast-developing subset of machine learning known as deep learning has proven to be just that. By mimicking the workings of the human brain, it seeks to identify patterns and predict outcomes in the real world. There are applications for models based on this type of neural network topology in almost every sector of the economy. Training such a model to make reliable predictions on any new test data is perhaps the most crucial stage of all the (integral) processes. To ensure that training is efficient in terms of time and fit (whether the model "knows" the training data too well or too poorly; to limit any form of overfitting or underfitting), it is important to choose a model's hyperparameters carefully[23].

The researchers will test a number of variables to see which will improve the accuracy of the model used, having identified which melting tests produced the most accurate results. In most cases, hyperparameters are static (they don't change during training) model variables that are provided by the user prior to training and that control the behaviour of the model and the overall architecture of the ANN[24]. In this study, the researcher also performed a manual hyperparameter turning process to identify good hyperparameters and tune them using different random state variables, number of epochs, dropouts, batch size, activation type and number of epoch. The details are listed in Table I.

TABLE I. MODEL TURNING EXPERIMENT DETAILS

Variables	Trials
Random state	0-100

Epoch	10-100
Batch size	32
	64
	128
	256

E. Hyper Parameter Turning

For this stage, the Bidirectional Long Short-Term Memory method is tested in classifying the final project title based on its grade. The test data consists of 266 data. In order to determine the degree of success in classifying the final project title, calculations are made [25]using a formula such as Equation (6).

$$Accuracy = \frac{Number\ of\ data\ detected}{Number\ of\ undetected\ data} \quad (6)$$

III. RESULT AND ANALYSIS

In order to assist the selection committee in classifying dissertation titles according to their grade, several experiments were conducted in this study to develop a classification model for dissertation titles. Specifically, two studies with different data labels were considered. In two different tests, the researcher compared the performance of the proposed model. For each of these cases, the experimental results are discussed below. Our technique was implemented in all experiments using the Python programming language and Google Colab.

A. First Experiment

First experiment related to different types of labels used by using the same number of attributes or variables in the model building process, the first type of label uses four (4) labels including; poor, fair, good and very good, resulting in an accuracy value of 56.46% and a loss of 88.21% for training data and for testing data resulted in an accuracy of 63.59% and a loss of 87.29 as in Fig.10.

```
Epoch 1/10
25/23 [=====] - 1s 70ms/step - loss: 1.1155 - accuracy: 0.5578 - val_loss: 0.9186 - val_accuracy: 0.6250
Epoch 2/10
23/23 [=====] - 1s 61ms/step - loss: 0.9591 - accuracy: 0.4938 - val_loss: 0.8989 - val_accuracy: 0.6250
Epoch 3/10
25/23 [=====] - 2s 69ms/step - loss: 0.9355 - accuracy: 0.5347 - val_loss: 0.9010 - val_accuracy: 0.6250
Epoch 4/10
23/23 [=====] - 1s 43ms/step - loss: 0.9279 - accuracy: 0.5333 - val_loss: 0.8784 - val_accuracy: 0.6250
Epoch 5/10
23/23 [=====] - 1s 37ms/step - loss: 0.9080 - accuracy: 0.5769 - val_loss: 0.8877 - val_accuracy: 0.6250
Epoch 6/10
23/23 [=====] - 1s 37ms/step - loss: 0.8997 - accuracy: 0.5565 - val_loss: 0.8855 - val_accuracy: 0.6250
Epoch 7/10
23/23 [=====] - 1s 38ms/step - loss: 0.9055 - accuracy: 0.5456 - val_loss: 0.8755 - val_accuracy: 0.6250
Epoch 8/10
23/23 [=====] - 1s 37ms/step - loss: 0.8971 - accuracy: 0.5633 - val_loss: 0.8780 - val_accuracy: 0.6250
Epoch 9/10
23/23 [=====] - 1s 37ms/step - loss: 0.9073 - accuracy: 0.5660 - val_loss: 0.8748 - val_accuracy: 0.6250
Epoch 10/10
23/23 [=====] - 1s 40ms/step - loss: 0.8821 - accuracy: 0.5646 - val_loss: 0.8729 - val_accuracy: 0.6359
```

Fig. 10. Accuracy and loss results from the first trial

B. Second Experiment

Whereas in the results of the second experiment by deleting data whose number of values is very far from other values and producing a dilation with the provisions that values from 67-79 belong to the "good enough" category and values from 80 to 95

are in the "good" category. In Fig. 11 conclude this experiment, in an accuracy value of 75.24% and a loss of 51.77% for training data and for testing data resulted in an accuracy of 68.85% and a loss of 60.18.

```
Epoch 1/10
23/23 [=====] - 5s 50ms/step - loss: 0.6296 - accuracy: 0.7004 - val_loss: 0.6807 - val_accuracy: 0.6940
Epoch 2/10
23/23 [=====] - 1s 22ms/step - loss: 0.6070 - accuracy: 0.7004 - val_loss: 0.6855 - val_accuracy: 0.6940
Epoch 3/10
23/23 [=====] - 1s 22ms/step - loss: 0.6026 - accuracy: 0.7004 - val_loss: 0.6811 - val_accuracy: 0.6940
Epoch 4/10
23/23 [=====] - 1s 24ms/step - loss: 0.5975 - accuracy: 0.7004 - val_loss: 0.5971 - val_accuracy: 0.6940
Epoch 5/10
23/23 [=====] - 1s 23ms/step - loss: 0.5866 - accuracy: 0.7004 - val_loss: 0.5916 - val_accuracy: 0.6940
Epoch 6/10
23/23 [=====] - 1s 22ms/step - loss: 0.5791 - accuracy: 0.7018 - val_loss: 0.5907 - val_accuracy: 0.6940
Epoch 7/10
23/23 [=====] - 1s 27ms/step - loss: 0.5663 - accuracy: 0.7073 - val_loss: 0.5958 - val_accuracy: 0.7213
Epoch 8/10
23/23 [=====] - 1s 30ms/step - loss: 0.5580 - accuracy: 0.7237 - val_loss: 0.5858 - val_accuracy: 0.7377
Epoch 9/10
23/23 [=====] - 1s 36ms/step - loss: 0.5392 - accuracy: 0.7308 - val_loss: 0.5935 - val_accuracy: 0.7213
Epoch 10/10
23/23 [=====] - 1s 28ms/step - loss: 0.5177 - accuracy: 0.7524 - val_loss: 0.6018 - val_accuracy: 0.6885
```

Fig. 11 Accuracy and loss results from the second trial

From the results of these experiments we can conclude that the second experiment has better accuracy results by using two labels, namely 'good enough' and 'good', because in the first experiment 'bad value' has a value that is very far from other data, so it can be one of the causes. But in this second experiment it still needs to be optimised again because the accuracy created is still not good enough to be used as a model. The method used in this research is to balance the data and rotate several parameters in the modelling to further optimise the accuracy.

C. Oversampling Dataset

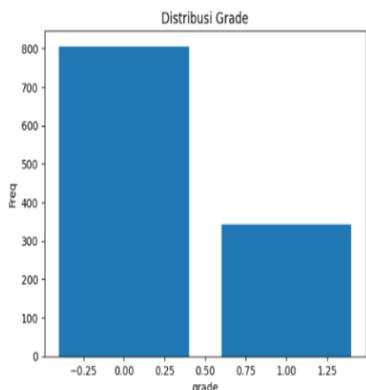


Fig. 12 The proportion of each label in the second experiment

It can be seen in Fig. 12 that the class grouping is not balanced, namely 804 data in the "good enough" class and 339 data in the "good" class, so it is necessary to balance the data. In this case, the researcher took the initiative to perform oversampling techniques on the data, also considering the limitations of this research, because deep learning requires a lot of data for the training process [26].

To solve the problem of classification on unbalanced data sets, this research has claimed [27] that oversampling is a method that is arguably superior to other methods because it can restore data balance while maintaining the characteristics of the original data. It does this by balancing data classes that have less data (minority) with data classes that have more data (majority). So, because the minority data is in the "good" class, the amount of data is balanced to the "good enough" class,

which is 804 data as in fig. 13.

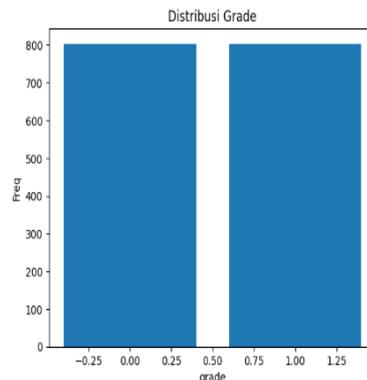


Fig. 13 Data after oversampling process

D. Turning Parameter

The next step is for the researchers to do further data processing to re-optimize the best temporary accuracy results by turning on several predetermined parameters, and the following are the best parameter results from several experiments.

The best result from several trials of Hyperparameter Turning on BiLSTM model building is by running trials with random state 10, Batch size 64 and use 100 epoch as shown in Table II. After all models have been built, the model is first configured using "Adam" optimisation and binary crossentropy optimisation to determine the loss value of the developed model.

TABLE II. BEST RESULT PARAMETER

Parameters	Best Results
Epoch	50
Random state	10
Batch size	64

Adjustments were also made to the construction of the Bidirectional Long-Term Memory model by adding a dropout layer in front of the hidden layer and giving the hidden layer relu activation. The details of the model building architecture are shown in Fig. 14 below.

```
# Sequential Layer
model = Sequential()
# Input Layer, Embedding Layer
model.add(Embedding(len(word_index) + 1, 300, input_length=x_train.shape[1], trainable=False))
# Dropout Layer 1 -> untuk mencegah terjadinya overfitting
model.add(Dropout(0.4))
# Hidden Layer
model.add(Bidirectional(LSTM(64, activation = "relu")))
# Dropout Layer 2 -> untuk mencegah terjadinya overfitting
model.add(Dropout(0.2))
# Dense Layer
model.add(Dense(64, activation = "relu"))
# Dropout Layer 3 -> untuk mencegah terjadinya overfitting
model.add(Dropout(0.4))
# Output Dense Layer -> untuk prediksi
model.add(Dense(1, activation="sigmoid"))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

Fig. 14 Model Architecture Details

Based on these conclusions, the researchers used the best results from the rotation process of several parameters mentioned above in the final project title classification model using the Bidirectional Long Short-Term Memory method, which resulted in an accuracy value of 90.18% and a loss of 24.72% for training data and for testing data resulted in an accuracy of 83.33% and a loss of 46.72% as in Fig. 15. And the graph of each epoch is as in Fig. 16, where in the graph image the loss model is stable between the loss of the training data and the test data. This shows that the model with the following parameters is a good model.

```
Epoch 46/50
17/17 [=====] - 2s 111ms/step - loss: 0.2994 - accuracy: 0.8774 - val_loss: 0.4124 - val_accuracy: 0.8527
Epoch 41/50
17/17 [=====] - 3s 198ms/step - loss: 0.2866 - accuracy: 0.8687 - val_loss: 0.4764 - val_accuracy: 0.8178
Epoch 42/50
17/17 [=====] - 3s 157ms/step - loss: 0.3042 - accuracy: 0.8755 - val_loss: 0.4232 - val_accuracy: 0.8296
Epoch 43/50
17/17 [=====] - 2s 141ms/step - loss: 0.2723 - accuracy: 0.8938 - val_loss: 0.4286 - val_accuracy: 0.8411
Epoch 44/50
17/17 [=====] - 2s 109ms/step - loss: 0.2502 - accuracy: 0.8959 - val_loss: 0.4411 - val_accuracy: 0.8333
Epoch 45/50
17/17 [=====] - 1s 85ms/step - loss: 0.2313 - accuracy: 0.9037 - val_loss: 0.4422 - val_accuracy: 0.8411
Epoch 46/50
17/17 [=====] - 1s 85ms/step - loss: 0.2725 - accuracy: 0.8901 - val_loss: 0.4111 - val_accuracy: 0.8411
Epoch 47/50
17/17 [=====] - 2s 144ms/step - loss: 0.2684 - accuracy: 0.8959 - val_loss: 0.4383 - val_accuracy: 0.8295
Epoch 48/50
17/17 [=====] - 2s 110ms/step - loss: 0.2594 - accuracy: 0.9056 - val_loss: 0.4813 - val_accuracy: 0.8372
Epoch 49/50
17/17 [=====] - 1s 80ms/step - loss: 0.2378 - accuracy: 0.9056 - val_loss: 0.4735 - val_accuracy: 0.8178
Epoch 50/50
17/17 [=====] - 1s 87ms/step - loss: 0.2472 - accuracy: 0.9018 - val_loss: 0.4672 - val_accuracy: 0.8333
```

Fig. 14 Results of accuracy and loss values

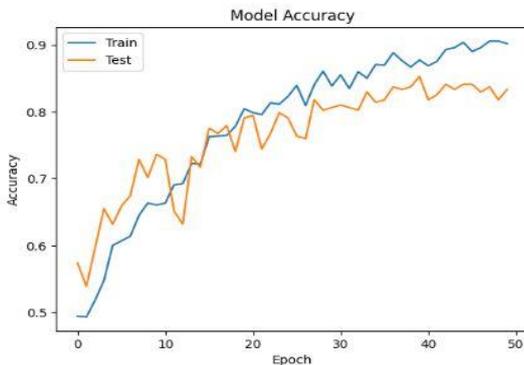


Fig. 15 Graph of best turning performance

And in Fig. 16, where the graph shows that the loss model starts to stabilise between the loss of train data and the test data. This shows that the model with the following parameters is a good model (no overfitting).

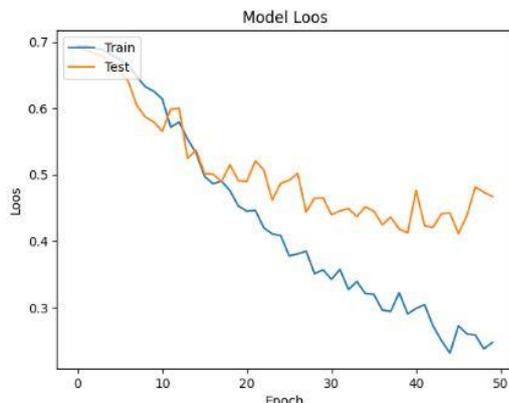


Fig. 16 Graph of loss model

IV. CONCLUSION

This paper presents an improved NLP model for the classification of final project titles based on their grade. The proposed model is based on the Bi-LSTM system, which is tested using two different labelling experiments performed on its dataset obtained from the lecturer's SIAMTEK account. The experimental results show that the two-category labelling has better accuracy and also the turning of some parameters in the model building. The proposed model can be used by the selection committee of Faculty of Engineering, Nurul Jadid University to help them to classify the final project title faster, thus facilitating them in the selection process.

In this study, the researcher performs an oversampling technique to balance the overlapping data and rotated several parameters in the model building, including random state variables, batch size, and number of epoch to improve the accuracy results. Until the best results were obtained by rotating several parameters, namely random state 10 times batch size of 64, and 50 epoch. This resulted can increase the accuracy.

In addition, in this study, we only used the values listed in the dataset in the process of determining the labels. However, this research has its own advantages and differences from previous research, namely in terms of the target classifier.

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