Measuring The Percentage of Brain Concentration Levels Using Bi-LSTM Algorithm

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***Abstract*—Human concentration plays a crucial role in affecting a person's activity. And it is very important to keep it present for people who need to do activities that require focus, for example, a surgical operator who needs to operate on a patient. But unfortunately, the measure of the concentration level in a person tends to be less clear. However, there is a way to overcome it by analyzing and observing the electroencephalography (EEG) signal generated by the human brain. The EEG signal will be used as training and testing datasets to automate the measurement of concentration level using the help of a deep learning approach. The model of deep learning will use the Bidirectional Long Short-Term Memory (BiLSTM) algorithm which is successfully able to measure the person's concentration level on a scale of 1 to 100. The model gained 82% as the minimum accuracy when tested on subject a's dataset and showed 93 % of accuracy as the best scenario for testing our model on subject b's dataset.**

Keywords—Human Concentration, Electroencephalograph, BiLSTM.

I INTRODUCTION

The level of concentration in carrying out an activity is very important to achieve the initial goal of the activity. As we know that with higher concentration levels, we can achieve superior benefits such as better grades, job performance, etc [1]. This has been proven from research that shows the relationship between concentration and academic achievement of students which supports the statement previously mentioned [2]. However, there is still no definite measure to classify a person's concentration level, so it is quite difficult to determine the level of human concentration on the activity he's doing.

However, there is one way to measure this concentration level accurately, which is by analyzing the data generated by the electroencephalographic (EEG) device [3]. Through an EEG device, the signals generated in the frontal and occipital lobes will increase depending on the concentration level of a person [4]. Through this information, we will automate the measurement of the human concentration level from the EEG data with the help of a deep learning algorithm so that we can accurately determine the concentration level of a person on a scale of 1 to 100.

The Measurement of concentration level can be implemented in various fields. For example, we can use it in the field of education, where a teacher can classify whether students in the class being taught are concentrating on the learning or not. Another example can be seen in the health sector, where we can classify whether the surgical operator who will operate can continue to concentrate on doing his work or not so that if the operator cannot concentrate any longer, he can be replaced by another surgical team. And there are many other things.

The need for this measure is important because we found so many accidents occur because of the lack of concentration in doing activities. That is the main reason why we made this paper. So, to accomplish this we are going to build and test a deep learning model which can classify the concentration level of subjects, using Bi-Directional Long-Short Term Memory (BiLSTM) algorithm in which measurements of concentration level are measured on a scale of 1 to 100. The purpose of the research is to test the accuracy of the proposed model in dealing with the problem that has been described.

This paper is organized as follows. First, we will discuss the literature review on the classification of brain concentration. Second, we will discuss the methodology that is designed and implemented in this research. Third, discuss the experiment and its result. Last, conclusion of the paper.

II LITERATURE REVIEW

The machine learning community likes to take part in developing an algorithm that is related to the cognitive function model. This type of algorithm is called "neuroscience-inspired artificial intelligence" [5]. One of the popular technologies that inspired this algorithm is the electroencephalogram (EEG). Electroencephalography is a non-invasive diagnostic method for analyzing bioelectrical brain function which the test relies on the placement of the electrodes on the skin surface [6]. It records changes in potential or differences in the potential of various parts of the brain and after appropriate amplification creates a record from them. This technology has a big opportunity for the application of artificial intelligence (AI). This can be seen from the many AI-based studies that aim to process EEG data to produce new models that can predict anything in the spectrum of the human brain [7].

In recent years, this EEG data has grown rapidly and has been the reason for increasing AI research related to the use of EEG devices. [8]. For example, we found several papers that have covered similar topics with different methods in them. Such as Support Vector Machine (SVM) which compare the use of two feature extraction which is Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) in predicting human concentration level, where the use of DWT gives higher accuracy than FFT with 91%

accuracy for the model [9]. Extreme Learning Machine (ELM) algorithm which uses the Hilbert Huang Transform (HHT) for feature extraction with 72% accuracy gained for the model [10]. But none of them try to use Bi-Directional Long Short-Term Memory (Bi-LSTM) algorithm although this algorithm is worth a try.

As we know, EEG signals are time sequence data that needs a model where it can process the type of time-series data [5]. Therefore, we need a neural network model which can overcome this problem, and the model is known as recurrent neural network [11]. But occasionally, the use of recurrent neural networks (RNN) shows unsatisfactory results. This has been proven by research conducted by Prabowo et al. (2019) where they have made a comparison between the basic RNN algorithm and the LSTM algorithm which shows that the use of the basic RNN performance has significantly far below the LSTM algorithm [12].

Furthermore, the LSTM algorithm has its improved version called Bidirectional Long Short-Term Memory (BiLSTM) where it can process the input data from 2 directions which are front to back and back to front. The BiLSTM algorithm can store important information and forget unnecessary information. Therefore, this process increases the accuracy of the model [13]. The similar study comes from Siami, Tavakoli & Namin (2019) which say that the BiLSTM-based modeling offers better predictions than regular LSTM-based models. More spesifically, it was observed that BiLSTM models provide better predictions compared to Autoregressive Integrated Moving Average (ARIMA) and LSTM models. It was also observed that BiLSTM models reach equilibrium much slower than LSTM-based models [14].

We already know that the BiLSTM algorithm has great performance compared to basic RNN, LSTM, and ARIMA to process time-series data. But it is not just only that, the BiLSTM performance compared to other algorithms such as SVM, MLP, and others show better results in every comparison. This has been proven by research from Balakrishnan, Idicula & Jones (2021) in comparing different algorithms for sentiment analysis [15]. The research was conducted by comparing 7 algorithms such as Naive Bayes, Logistic Regression, AdaBoost, SVM, Convolutional Neural Network (CNN), LSTM, and BiLSTM. They found that BiLSTM gave the highest F1 score with a score of 0.919, followed by LSTM with a score of 0.902, then CNN 0.877, SVM 0.869, AdaBoost 0.786, Logistic Regression 0.721, Naive Bayes 0.743. Furthermore, another research conducted by Dang, Troia, & Stamp (2021) in comparing Multi-Layer Perceptron (MLP), LSTM, BiLSTM, CNN-BiLSTM [16] shows the same result, where BiLSTM wins against MLP and LSTM, but the interesting thing is CNN-BiLSTM gives better performance than the BiLSTM algorithm. This makes us assure that the usage of BiLSTM in classifying the EEG signal will give magnificent results in the future.

With various studies that have been described, we will conduct an experiment to develop a model which can measure the user's concentration with a scale of 1 to 100 using the BiLSTM algorithm. As our aim here was to build and test the BiLSTM algorithm used and deploy it on a scale of 1 to 100, an experimental approach was required. Hence, we carried out two experiments. In the first one, we will give the output of each input value entered the model, where the values are in the range of 0 to 1, which is the result of the sigmoid activation function. The output values from the model will be averaged to determine the result of the brain concentration measure. The result will be multiplied by the value of 100 so that it can be changed to the scale we wanted. Later in our second experiment, we will test the model accuracy. We will round up the existing values into 3 classifications. First, label 0 which means relax concentration for data in the range of 0.0 to 0.2. Second, label 0.5 which means normal concentration for data in the range of 0.3 to 0.7, and label 1 which means high concentration for data in the range of 0.8 to 1. The rounded value will be compared to the real output of the sets.

III METHODOLOGY

A. System Design.

The input dataset used in this study was collected from Bird et al (2018)'s EEG dataset which provides a raw EEG dataset on each state of subject using a muse headband [17]. This input dataset will be prepared using the rolling windows and data transforms method so it can fit on our model. Bidirectional Long Short-Term Memory (BiLSTM) is used as our model algorithm to process the input data according to the defined model. The output of each input will be averaged to get the user's concentration level. The system block diagram is depicted in Figure 1.

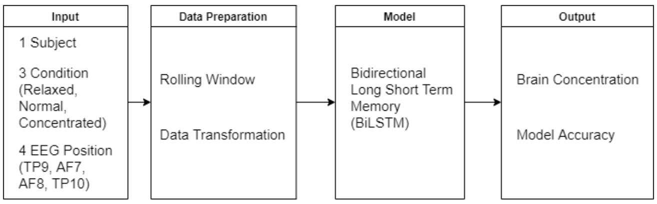

Figure 1. Block Diagram

B. Input.

The technical term of Electroencephalography (EEG) signal can be referred to as a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex [18]. This signal can be used to analyze many aspects of the psychological and biological changes in the human mind, such as, to analyze neurological diseases, arousal detection, and brain performance detection.

For this paper, we will predict brain concentration by analyzing this signal. Manually, we tried to predict the concentration level of the brain by analyzing which type of signal it was producing [3]. For example, when an EEG signal shows delta waves, it can be indicated that the person has a low concentration level. Furthermore, when beta waves are shown, it can indicate that a person has a medium/neutral concentration level. And finally, when an EEG signal shows gamma waves, the person can be indicated that he/she has a high concentration level.

The first step to conduct this research is to acquire the raw EEG dataset. We obtain the dataset from Bird et al (2018)'s EEG dataset [17] which provides raw EEG datasets of 4 subjects in 3 conditions which are 'concentrating', 'relaxed', and 'neutral'. For one minute timestamp, each subject will be scanned with an EEG device while doing each of the states provided. But unfortunately, after some analysis we found that 2 of the datasets has noise inside it. So, we decided to use only 2 subjects from the 4 available subjects given which are subject A and subject B. The device will record the four channels from the subject's head, which are TP9, AF7, AF8, and TP10. And these four channels will be collected and represented as the features of our model.

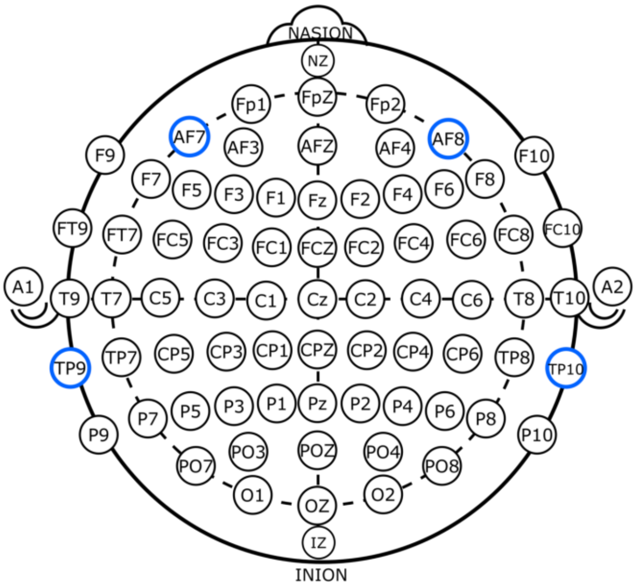

Figure 2. The EEG electrode placement, highlighted in blue.

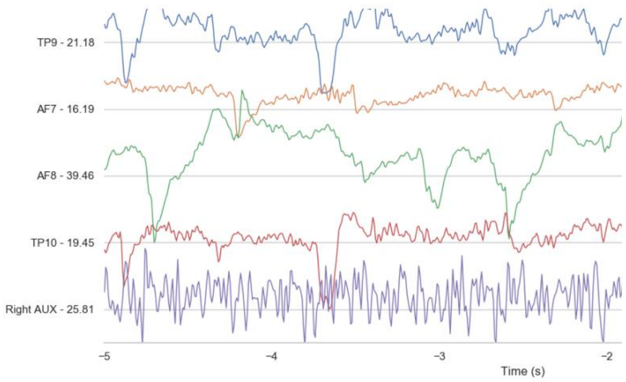

Figure 3. Bird et al (2018)'s EEG dataset, Right AUX did not have a device and was discarded due to it simply being noise [17].

Table 1. Dataset Information

	Subject A	Subject B
Columns	6	6
Rows	15104	15104
Timestamp	1 minutes	1 minutes

C. Data Preparation.

There are two main steps to do in the data preparation which is the rolling windows, and data transformation process. The purpose of data preparation is to make sure the datasets are eligible to be used in our model. Our models were made by the BiLSTM layers consisting of 128 layers, where each layer has 100 cells, and each cell has four inputs, which are our features in the dataset.To put the features into the model, we need to use the rolling window approach, this approach is intended to capture data into sequences of data with every next sequence having n+1 of 100 data, which is our total amount of the cell in the BiLSTM layers.

The second step is data transformation, first we need to merge the dataset in different condition states which are concentrate, neutral, and relax states then assign the label for each condition. The labels are assigned for each condition with the following rule. First, the relaxed state will be labelled as 0. Then, the neutral state will be labelled as 0.5. And last, the concentrated state will be labelled as 1. And finally, the input and output can be fitted into the model.

D. Model Analysis & Training.

For this phase, we tried to develop and identify the model so it can classify our data to produce the measurement of brain concentration. For the input, we are using one dataset which has been prepared using rolling windows and data transforms methods. The first datasets will be trained, and the other dataset will be tested, and we will try to do this training on each dataset to make sure about our model. Then we use the BiLSTM layer to process the time series-based dataset.

The important aspect of BiLSTM is it consists of two vanilla LSTMs that process a forward time sequence, and the other processes a backward time sequence. Each LSTM cell features three types of gates, which are input, forget, and output gates. There are also a single cell, activation function, and peephole connections [19]. The operation of an LSTM cell consists of forwarding pass and backward pass. The forward pass is conducted with the aim of processing the input into output. Meanwhile, backward pass, in this case, backpropagation through time (BPTT), is performed for the purpose of decreasing the loss by optimizing the parameters in the LSTM architecture.

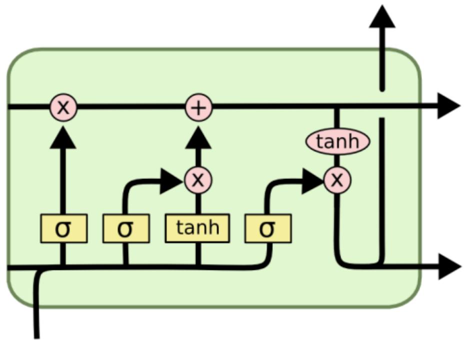

Figure 4. Single cell LSTM

There are six operations that need to be done on the forward pass. The input is going through the neuron on the block input cell into the forget gate. The formula is shown below.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

The calculation consists of the weights of the neuron, multiplied by the input and block output of the previous time step, and summation by bias. Then, we can go to the logistic sigmoid function below.

$$f(x) = \frac{1}{1 + e^{-(x)}}$$

The second operation is done by forwarding the input into the input gate and the forget gate. The formula is shown as below.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Below is the calculation of the input gate. The formula consists of the multiplication of the input, weights, block output of the previous timestep and summation by bias. The next step is to calculate the forget gate by a formula below.

$$\hat{C}_t = \sigma(W_C \cdot [h_{t-1}, x_t] + b_C)$$

The formula is about the same as the previous formula. Now, calculate the single cell by the formula below.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \hat{C}_t$$

The formula is explained by the summation of the previous calculation, which is the block input cell, multiply by previous cell, and sum by the multiplication of input gate and forget gate. And finally, we calculate the output gate by formula below.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

The calculation is about the same as the previous input formula. Finally, we multiply the output gate with the result of the cell formula with the activation function of tanh, which is defined by calculation below.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

And the calculation of the block output is defined below.

$$h_t = o_t \cdot tanh(C_t)$$

For the backpropagation, it tries to optimize the weights by calculating the delta of weights. The delta of weights found by the changes of all weights should be proportional to the gradient descent, which is the same as the delta learning rule. Now, we can define the input dimensions.

Because each row has an interval of 0.4 second, with a total dataset of 1 minutes, the model must process a long term-dependency of data, which can be solved by a rolling window method. Each sequence will be put into the input layer of the BiLSTM layer with a total layer of 128. After that, the output of the BiLSTM layer will be concatenated between forward step and backward step, the result will be forwarded to multilayer perceptron (MLP) with 64 neurons. To predict the percentage of concentration, our output must be on the scale of 1 - 100 percentages. Thus, the output neuron of the model must produce a number between 0 and 1, which can be solved by a sigmoid activation function formula. The output layer will be connected to 64 neurons of MLP earlier. And with the sigmoid activation function, output will be produced.

After feed forward, The model will be back propagated with Adam optimizer and mean square error with the purpose of improving the accuracy and decreasing the error. Training will be done for two epochs. This process will be producing the final model, validation accuracy, and model accuracy.

E. Data Testing.

After the model has already trained, we need to test the trained model. This process intended to validate the model's capability to process new data. In our case, we will use the first subject's dataset as the train dataset, leaving the second subject as the testing set. We will test each dataset to make sure the model did well and validate it using accuracy metrics.

To find the accuracy of the model, first we need to round up the output of each value to become 3 labels, where label 0 means relax concentration for data in the range of 0.0 to 0.2. Then, label 0.5 which means normal concentration for data in the range of 0.3 to 0.7, and label 1 which means high concentration for data in the range of 0.8 to 1. After all of the values are rounded up, we will validate it with metrics accuracy to get the testing accuracy and visualize it as the output for the work.

F. Output

Output of this study is the brain concentration level on the scale of 1 to 100 and model's validation. For the model's validation, the process is mainly used to visualize the obtained validation, so it would be easier to analyze the validation in visualized output. In this paper, the validation result will be presented in the form of a validation accuracy, and confusion matrix.

IV RESULT

The result obtained by our BiLSTM model shows the following result as the table below.

Table 2. Experiment Result

Training dataset	Test dataset	Training_accuracy	Testing_accuracy	Concentration_level
subject a	subject b	66%	**93%**	**51%**
subject b	subject a	61.2%	**82%**	**55.3%**

The concentration level for each test subject seems to be almost similar because we merge all of the 3 conditions states which are concentrate, normal, and relax into the same dataset where it means the concentration level will be gained from the average of all of that state.

From the table above, we can see that the model has performed quite well when trying to predict each other's dataset. It shows accuracy above 80% for each subject in the testing. More specifically, it's reported to give 93% accuracy as the best scenario for the model, and 82% accuracy as the minimum scenario for the model. The official metric for evaluation in our model is metrics accuracy. As can be seen from the table, the BiLSTM classifier performed so well with ~64% accuracy for training data, indicating the model has learned and tried to predict the training data. After that, we predicted the test dataset for each subject and found that it can predict each sequence and its output with an accuracy above 80%

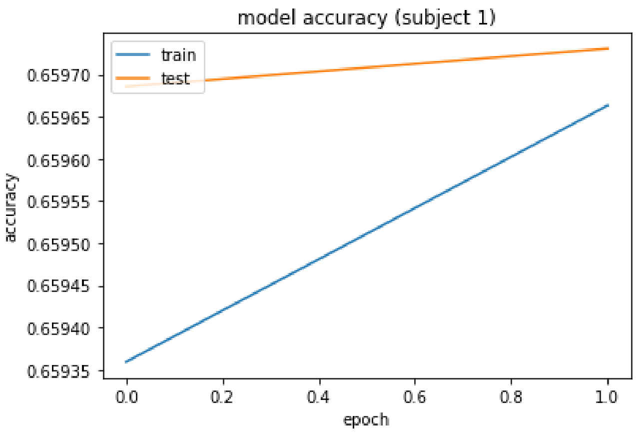

Figure 5. Best model's validation accuracy

It has been shown in figure 6 that the test validation has better accuracy than the training validation. The reason why the test validation has better accuracy than the training is because we assigned the labels into three classes manually, when our aim is to predict 1 - 100 scale of brain performance. When the training process is conducted, it will train with the label which is proportional to the error, when it should be proportional to 0 - 1 scale output, which is the reason the accuracy is a little bit low. Because of this, we rounded the output to the nearest label to validate our trained model and obtained a high accuracy.

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The time taken for the training of this model's quite long, in our model the training runs with the speed of 165 ms / step which the total time to be used for training is 814 seconds. Then considering that our training epoch is 2, we estimate that the accuracy can be improved by training the model with more epoch. The reason is the gradient descent optimization has not reached its maximum optimization yet, as shown in the validation accuracy plot. Because of this reason, we recommend that the maximum epoch of the training model be improved and will be a record for us in the future.

V CONCLUSION

This paper reported the results of experiments and showed that the model proposed successfully was able to measure the concentration level of the subject. The performance and accuracy of the proposed model gave satisfaction results with the highest accuracy in testing the model was 93%. And the minimum accuracy for the model was 82%. The results showed that the use of BiLSTM algorithm in classifying the concentration level is a good step in building the desired model. We noticed that training based on BiLSTM is slow and it takes fetching additional batches of data to reach equilibrium, but the time needed to train the model is worth the accuracy. As a result, this paper recommends using the BiLSTM algorithms for the model of classification in measuring the brain concentration level compared to other algorithms because of its high accuracy. This research can be further expanded to classifying the forecast of EEG signals to determine the time needed for the brain to be concentrated.

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