Journal of Telecommunication, Electronic and Computer Engineering
ISSN: 2180 – 1843 e-ISSN: 2289-8131 Vol. 16 No. 1
jtec.utem.edu.my
DOI: https://doi.org/10.54554/jtec.2024.16.01.004

Microsleep Predicting Comparison Between LSTM and ANN Based on the Analysis of Time Series EEG Signal

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Article Info

Article history:
Received Feb 2nd, 2024
Revised Feb 25th, 2024
Accepted Mar 19th, 2024
Published Mar 31st, 2024

Index Terms:
Microsleep Prediction
EEG Signal
ANN
LSTM

Abstract

A microsleep is an unintentional, transient loss of consciousness correlated with sleep that lasts up to fifteen seconds. Electroencephalogram (EEG), recordings have been extensively utilized to diagnose and study various neurological disorders. This study analyzes time series EEG signals to predict microsleep employing two deep learning models: Long-Short Term Memory (LSTM) and Artificial Neural Network (ANN). The findings show that the ANN model achieves outstanding metrics in microsleep prediction, outperforming the LSTM in key performance metrics. The model demonstrated exceptional performance, as demonstrated by the outcomes of the Scatter Plot, R2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Between the two models, the ANN model achieved the most significant R2, MAE, MSE, and RMSE values (0.84, 1.10, 1.90, and 1.38) compared to the LSTM model. The critical contribution of this study lies in its development of comprehensive and effective methods for accurately predicting microsleep events from EEG signals.

I. INTRODUCTION

Microsleeps are short (≲ 15 s) unintentional gaps in conscious correlated to sleep in which an individual briefly nods off and stops functioning [1]. They have been associated by drooping eyes, ocular closure behavioral indicators, and complete loss of visuomotor response [1][2], they differ significantly from the additional tonic stages of fatigue (refusal to respond) and drowsiness (tendencies toward falling sleep) [3] – [5]. Research has demonstrated that people in good health who do not suffer from sleep deprivation can also experience frequent microsleeps [1][4]. Moreover, a significant relationship has been reported between the possibility of accidents and the duration of microsleeps [6]. When engaging in prolonged, tedious responsibilities like driving, microsleeps can have deadly repercussions. However, once they can be properly and noninvasively predicted, these accidents can be minimized.

Microsleep can be triggered by a variety of factors, such as insuffient sleep or illnesses like narcolepsy or sleep apnea, but it frequently happens during monotous tasks or due to lack of quality sleep (refer Figure 1). Additionally, they are also frequently induced by physical and mental exhaustion, disruptions in circadian rhythms, and boredom from repetitive activities [7]. Such episodes can also occur in well-rested individuals who perform repetitive tasks without prior signs of fatigue [8]. Individuals who were involved in accidents related to microsleep may be unaware of their pre-accident drowsiness or the brief lapses in consciousness or attention, owing to adrenaline masking their fatigue post-incident. This raises significant issues regarding security, particularly for individuals who work in high-risk occupations demanding persistent, prolonged visuomotor performance such as driving, flying, navigating, maritime transport, and process control. Therefore, effective monitoring for signs of impending microsleeps could be crucial in preventing catastrophic events and saving people's lives. Microsleep is problematic since it happens unexpectedly and inadvertently [9].

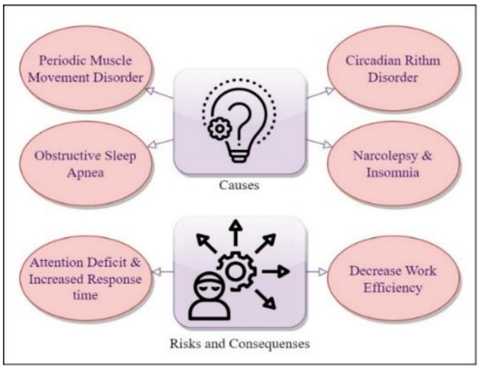

Figure 1. Causes, risks and consequences associated with microsleep.

Machine learning and deep learning have been employed in multiple research investigations aimed at identifying micro-surges in electroencephalogram (EEG) data. Latest advancements, such as algorithms based on deep learning that are capable of extracting, evaluating, and collecting information gathered from unstructured information, provide the complete solution. With deep learning, more emphasis could be placed on the development of models to improve the effectiveness of microsleep prediction [10][11]. The performance of these models greatly depends on the selection of features. Customized features are those that have been generated from data by a particular assembled procedure that is found on specialized expertise. This could limit the representation of the traits and indicators found in the data. Alternatively, learning-based features are derived directly from the data through training processes aimed at achieving specific objectives. This paper aimed to develop a robust microsleep prediction method that might serve as the basis for a real-time alert system, thereby preventing catastrophic mishaps by warning individuals of their state of alertness.

II. UNDERSTANDING MICROSLEEP

The background information regarding the manifestation and predictions of microsleep is included in this section.

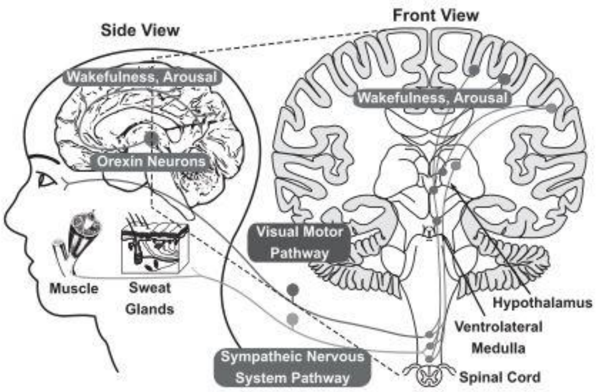

Figure 2. Neuronal mechanism of consciousness [12].

A. *The Manifestation of Microsleep*

Figure 2 illustrates the Orexin structure, a wakefulness network encompassing the entire central nervous system. It increases the functioning of neurons in the visual cortex, cerebral cortex, and the middle brain region. Brain waves serve as an indicator of these neural activities. During wakefulness and consciousness, the brain produces rapid Beta (β) and Alpha (α) waves; during sleepiness, the brain produces slow Theta (θ) waves. Further research in animals has demonstrated that Orexin neurons control the measurement of the pupil, the positioning of the eyelids, and perhaps the convergence and orientation of the eyes through motoneurons in various muscle fibers [13].

Thus, the activity and movements of the eyes also serve as a representation of the wakeful condition. Furthermore, additional investigation [14] has demonstrated that orexin controls wakefulness in the autonomous nervous system (ANS) by stimulating the ANS by conducting projections to the spinal cord and ventrolateral medulla, which inhibits sleep. Changes in sweat gland activity and facial muscle movements can be signs of the sympathetic nervous syatems' response, which is influenced by Orexin's regulatory function.

B. *Microsleep Prediction*

The crucial aspect to capturing the transition from awake to sleep is microsleep, which is the brief period of abandoning consciousness. People are still capable of waking up following a microsleep episode, which can last somewhere from a few to fifteen seconds. The behavioral and electrical manifestations of microsleep include slow rolling of the eyes, eventual closure of the eyelids, and head nods [1]. Electrical manifestation is a change in electroencephalography (EEG) from fast α and β waves to slower θ activities [15]. The aforementioned symptoms are related to the Orexin system being inhibited. People who have excessive daytime sleepiness frequently experience this issue. Since most people who experience microsleeps are unaware of what is happening and still think they are awake the entire time, microsleep is quite risky for activities that require continuous concentration [12].

III. RELATED WORKS

Comprehending the features and nuances of the EEG data linked to brain activity across a variety of circumstances is necessary to for the identification of microsleeps [16]. Additional research into the use of EEG for detecting microsleeps is needed, given that EEG record electrical potentials and offer insights into brain function. This easy test demonstrates how the brain evolves gradually [17]. Researchers and medical practitioners routinely utilize EEG to examine the functioning of the brain and pinpoint neurological issues. EEG is a vital component of contemporary studies in multiple areas. This medical approach can be used in determining an individual's brain death, the degree of damage of a stroke or injuries to the head, epilepsy activities, difficulties with sleep, and numerous other issues. It can be beneficial in linguistic and clinical research on conditions like aphasia, as well as in other studies looking into other cognitive functions like memory or attention [18][19].

Professionals typically conduct visual assessments to score sleep stages over an extended duration, but automatic identification is preferred for diagnosing and treating sleep-related disorders. A 'response lapse' occurs when an individual lacks the ability to react to an activity that is in progress. Blackouts can take numerous distinct shapes, depending on the underlying cognitive functions. While some errors result in wrong outcomes, others induce impediments in providing a prompt solution. Absolute sensory-motor collapses can happen as a result of some blunders. Attention lapses occur during situations where there is a momentary disruption that hinders or stops the person from reacting to the primary task without resulting in unconsciousness [20]. An individual may in some circumstances inadvertently perform a supplementary task, such as walking, looking, or driving during such a lapse. Microsleep is when an undesired decline in concentration associated with sleep occurs. For a brief period of duration, the person moves into the light sleepy phase. Microsleeps manifest behaviorally as partial eye closing, head nodding, and inadequate facial expressions. However, a period of inactivity lasting over thirty seconds typically falls under the category of sleep [21][22].

Several classifiers and a combination of features have been utilized to achieve the existing standards in monitoring the microsleep state, which represents the best performances for recognizing microsleep stage in raw data. However, despite a plethora of research, no approach has yet reached the level of efficacy that allows for widespread practical application [23]. Convolutional neural network (CNN) topologies of various configurations were used to evaluate the accuracy of data from the electroencephalogram (EEG). Deep recurrent convolutional neural networks are utilized to generate learning representation which are effective and resistive to both inter and intra-subject variations and inherent EEG interference [24]. Deep neural networks, an unsupervised feature learning architectural design, were deployed to the sleep data in order to eliminate the necessity for manually created features [25].

Poudel et al. [26] revealed that when sleep is restricted, the likelihood of falling asleep gets higher. Nevertheless, researchers discovered no association between the prevalence of microsleeps during regular slumber and following sleep deprivation [27]. Investigations have been done on EEG-based microsleep identification in [28][29]. Power spectral feature, fractal dimensions, estimated entropy, and Lempel-Ziv complexity of EEG have been determined by Peiris et al. [28]. In order to identify microsleeps, they stacked six linear discriminant analysis classifiers and created meta-features using PCA. A similar technique was applied by Davidson et al. [2], but with long-short-term-memory (LSTM) recurrent neural networks. In order to prevent overfitting and lower complexity of computation, PCA was utilized to limit the feature count to thirty. However, research has demonstrated that deep learning techniques outperform traditional machine learning approaches when analyzing EEG data [30][31]. The benefits of machine learning, and particularly deep learning, have spurred substantial development in sleep and its related identification [32-34]. In considering this, we decided to conduct this investigation using the LSTM and ANN models.

Previous research produced significant results for the detection of microsleeps. A flat response in tracking along with eye-closure identification apart from face-video was used to characterize microsleeps. Furthermore, earlier studies limited themselves only to the detection of microsleeps. To the best of our knowledge, the literature has not delved into microsleep predictions in greater detail. Our current research aims to fill this gap by predicting the occurrence of microsleeps.

IV. METHODOLOGY

The comprehensive design of the current investigation system is shown in Figure 3, which illustrates the sequential processing steps performed on the time series EEG data to predict microsleep for both models.

A. Data Description

The EEG dataset, which is available online and referenced in [35], was used in this study. This dataset, collected with a driving simulator during nighttime sessions, records brain activity and includes critical microsleep characteristics, serving as a basis for training predictive models. To record brain waves while operating an automobile, the data is recorded overnight in a simulator. It captures brain activity of when the driver is awake and consciously driving, when the driver is drowsy and when the driver has gone into microsleep. Our methodology involves preprocessing the data, loading it into a data frame iteratively, and then using a generator function for efficient model input. In order to estimate brain activity and predict potential instances of approaching microsleep occurrences, every file in the dataset adds to the overall understanding of overnight driving circumstances.

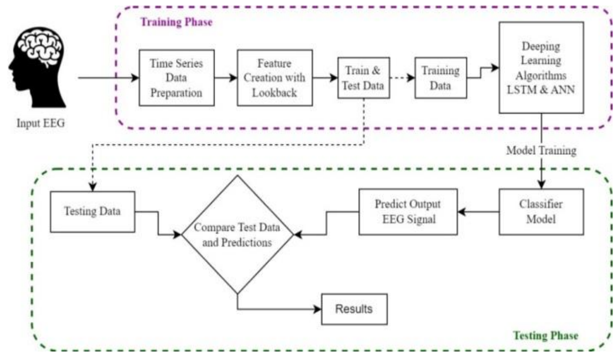

Figure 3. Comprehensive design of the current investigation.

Through this iterative approach, memory utilization is optimized, and information is seamlessly transferred to the model, enabling it to learn from and generalization from a variety of brain function examples under simulations involved driving situations. Consequently, the model acquires the capacity to predict and perhaps avert microsleep incidents, augmenting safety and efficiency in prolonged driving situations. The incorporation of a generator function enables instantaneous analyzing, rendering it an advantageous instrument for ongoing observation and interventions in scenarios where microsleep occurrences provide a noteworthy risk.

B. Data Processing

Preprocessing the dataset for this study entails an organized sequence of procedures to prepare the data for training and assessing deep learning models. Initially, a particular channel is carefully selected from among the many channels in the dataset. Pertinent information related to the chosen channel is then taken from all of the accessible data files. The extracted data from each file is smoothly concatenated, joining the data from one file head-first to the tail of the preceding file, to produce a coherent dataset. This process results in the generation of a consolidated dataset, named "all_data.csv," which encompasses the combined information from all data files pertaining to the chosen channel. We have introduced additional 32 features generated by considering historical data through a lookback mechanism, enabling the training process to leverage insights from past information.

Following dataset consolidation, the data is partitioned into training and testing sets, allocating 80% for training and reserving the remaining 20% for model evaluation. The final step involves feeding the prepared dataset through a deep learning model, facilitating the extraction of intricate patterns and relationships within the time series data for predictive analysis.

C. Classification Model

Two deep learning methods have been employed for the classification task. These include Long Short-Term Memory (LSTM) and Artificial Neural Networks (ANN). Below is an assessment of the functioning structures and architecture.

Long-Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, perform very well in time series prediction because of their capacity to recognize and retain long-term dependencies. Recurrent neural networks are highly efficient time series prediction networks that possess internal memory. Every neuron in recurrent neural network transmits information to each subsequent neuron in its layer. The shortcomings of the recurrent neural network cell are addressed by the LSTM extension of the recurrent neural network cell [36]. LSTMs reduce vanishing gradient issues with complex memory cells, which improve their modeling performance for sequential data [37].

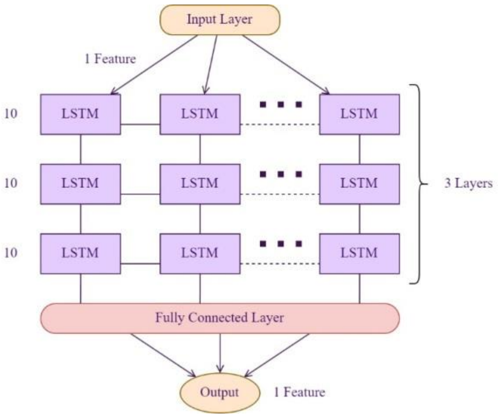

Figure 4. Architecture of LTSM Model

The three gates that make up an LSTM cell are:

- The sigmoid gate, which determines what data should be kept and what should be deleted, is part of the keep gate.

$$f_t = \sigma(w_f\ [h_{t-1}, X_t + b_f]) \quad (1)$$

Where, f_t = forget gate's output.; σ = function of sigmoid; w_f = function of weight; h_{t-1} = input from the preceding cell; X_t = the cell's input and b_f = bias.

- The write gate stores the necessary data in the memory. It is employed through:

$$i_t = \sigma(w_f[h_{t-1}, X_t + b_f]) \quad (2)$$

$$\tilde{c}_t = \tanh\,(w_c[h_{t-1}, X_t + b_c]) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (4)$$

Where, i_t = outcome of the write gate's sigmoid layer; c_t = new cell state; c_{t-1} = old cell state.

- The output gate determines what should be output.

$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o) \quad (5)$$

$$h_t = o_t * \tanh\,(c_t) \quad (6)$$

where, o_t = sigmoid layer output in the output gate; h_t = the LSTM cell's output.

The fundamental EEG data's extracted time domain feature, which contains all of the concatenated data, is incorporated into the input data. Three LSTM layers, each containing 10 hidden neurons, make up the LSTM model. The output has been augmented with a thick layer. The structure of implementation of LSTM architecture is depicted in Figure 3. The Adam optimizer was used to fit the model after it had been trained for 50 epochs using MSE as the loss function. The Python model was implemented using Pytorch.

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are an assortment of machine learning models that draw inspiration from the neural architecture of the human brain. When it comes to time series data prediction, simple ANN without convolutional or recurrent layers show their abilities. An input, hidden, and output layer compose the architecture of a fundamental ANN, and information flow is facilitated by connecting nodes and regulated connections. Through the use of backpropagation, this neural network adjusts its weights as it discovers connections and patterns in historical time series data [38].

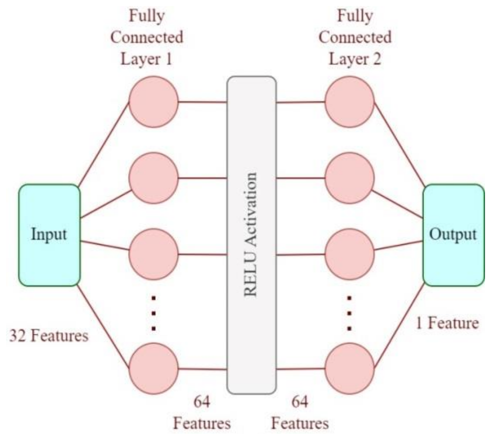

Figure 5. Architecture of ANN Model

This method employs a relatively rudimentary ANN model with two fully connected layers and a Relu Activation layer. The first linear layer receives the input EEG data and processes it, taking 32 input features and producing 64 output features. After that, it is run through the non-linearity detecting Relu Activation layer. Since only one prediction value is required, the data is then sent through a second linear layer that accepts 32 input features and produces one output feature. Employing Adam as the optimizer and MSE as the loss function, the model was trained for fifty epochs.

By combining the weights and biases with the transfer function, a trained artificial neural network (ANN) model can be mathematically expressed. A typical expression for the mathematical equation linking the input and output parameters is Equation (7) [39].

$$Y = f_{sig}\left\{b_o + \sum_{k=1}^{h}\left[w_k \times f_{sig}\left(b_{hk} + \sum_{i=1}^{m} w_{ik}X_i\right)\right]\right\} \quad (7)$$

where b_0 = bias in the output layer; w_k = connection weight between the kth of the hidden layer and the single output neuron; b_{hk} = bias at the hidden layer's *k-th* neuron; h = neurons number in the hidden layer; *wik* = connection weight between the *i-th* input variable and the hidden layer; X_i = normalized input variable i; Y = normalized output variable; f_{sig} = transfer function.

Because ANN can capture the intricate nonlinear connections present in temporal data, it has shown effectiveness in time series prediction. An adequate-sized neural network is capable of approximating any continuum function, according to the universal approximation theorem, which is why ANNs are exceptionally effective at identifying complex patterns in time series datasets.

D. Loss Functions and Evaluation Criterion

For the purpose of obtaining the trained network, two distinct loss functions were applied. Initially, the network was trained with the Mean Squared Error (MSE) loss as given in Equation (8). This loss had been optimized using the Adam optimizer at a learning rate of 0.001.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{8}$$

The model was adjusted by training it again using the R^2 loss specified in Equation (9), following the initial training phase.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \tag{9}$$

A learning rate of 0.001 was employed in the optimization process utilizing the Adam optimizer. The maximum number of epochs for both training instances was fixed at 50.

Due to the work's objective of employing LSTM and ANN models to predict the microsleep as closely as possible, measures measuring the similarity within the predicted and the actual signals were required. The measure used for evaluation to compare with the overall quality of current literature was the R^2 score. For improved assessment, parameters such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) have been assessed in addition to the R^2 score. The remaining two metrics below are determined by equations (10) and (11).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{10}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{11}$$

Where, $\hat{y}$ = predicted value of y and $\bar{y}$ = mean value of y.

V. RESULT AND DISCUSSION

We compared the two models using a variety of measures, including the Scatter Plot of R2, R2 Score, MSE, MAE, and RMSE, to demonstrate the comparative performance of the study. The significant relationship throughout two variables can be comprehended and interpreted using the scatter plot. In order to display the data as an integrated model and enhance comprehension of the examined data, this is the recommended data visualization tool. Figure 6 and 7 show the scatter plot of LSTM and ANN model respectively. The scatter plot of the LSTM model (Figure 6) shows a positive bias, where the predicted values are consistently lower than the actual values. This means that the model is underestimating the true values. The R-squared score of 0.8297 suggests a good overall fit, but it is important to consider the bias when interpreting the results. The scatter plot of the ANN model (Figure 7) shows a negative bias, where the predicted values are consistently higher than the actual values. This means that the model is overestimating the true values. The R-squared score of 0.8339 is slightly higher than the LSTM model, but again, the bias should be taken into account.

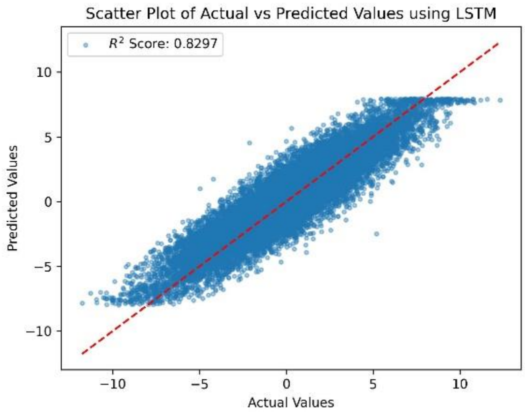

Figure 6. Scatterplot of LTSM Model

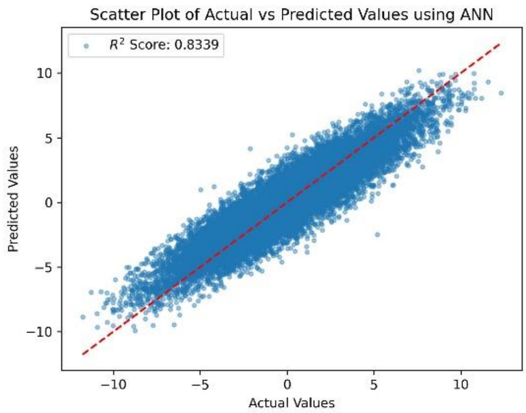

Figure 7. Scatterplot of ANN Model

However, the spread in the LSTM model appears to be slightly wider than the spread in the ANN model.

From the time series EEG signal, we predicted microsleep employing LSTM and ANN model. Figure 8 illustrates the outcome for the time series EEG data acquired in a driving simulator environment that was predicted using the LSTM model. In a similar way, Figure 9 indicates the ANN model's predicted output.

LSTM model seems to have captured the overall trend of the actual output well in the initial part of the prediction. However, there is a significant divergence between the predicted and actual values towards the latter half of the plot. This suggests that the LSTM model may have difficulty in making accurate predictions for longer time horizons. On the other hand, ANN model also seems to capture the initial trend of the actual output well. However, there is a notable divergence between the predicted and actual values throughout the entire prediction, with ANN model consistently underestimating the actual output.

LSTM model shows a larger divergence from the actual output towards the end of the prediction compared to ANN model. The ANN model consistently underestimates the actual output throughout the prediction, while the LSTM model shows a mix of underestimation and overestimation.

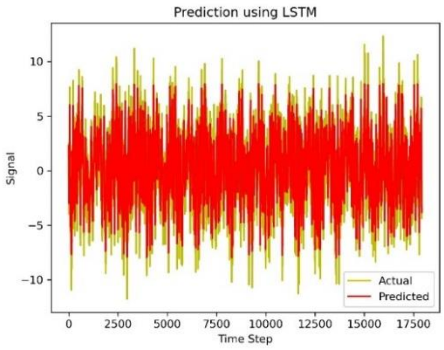

Figure 8. Predicted output using LSTM model.

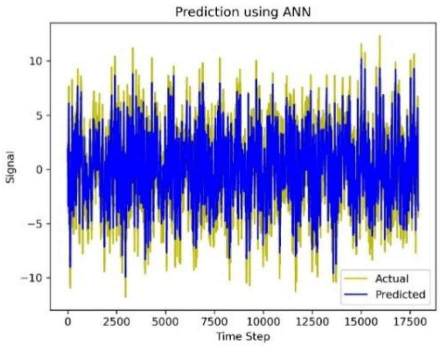

Figure 9. Predicted output using ANN model.

Figure 10 illustrates the predictions of all of the measures that were evaluated for both models. The R^2, MAE, MSE, and RMSE metrics that were utilized in the LSTM model's prediction of microsleep by utilizing the time series EEG signal have the following values: 0.82, 1.12, 1.96, and 1.40 respectively. Whereas the R^2, MAE, MSE, and RMSE values of the ANN model have the following values: 0.84, 1.10, 1.90, and 1.38 respectively.

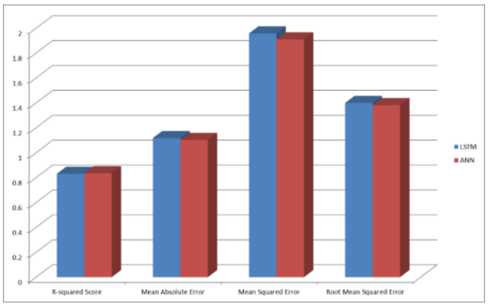

Figure 10. Performance metrics comparison of both models.

Figures 6 to10 illustrate the fact that both LSTM and ANN models can predict microsleep quite effectively. We can infer from the performance metrics' numbers and values that the ANN model outperformed the LSTM model in predicting microsleep.

VI. CONCLUSION

The objective for this study was to use EEG time series data to determine and compare the potential for prediction of ANN and LSTM models for microsleep. As time went on, it became apparent that both LSTM and ANN were sufficient for microsleep prediction. Following a number of tests, the artificial neural network (ANN) demonstrated higher predictability in its calculated values. This suggests that the ANN model may be employed for time series data to accurately predict microsleep using EEG signals, which can significantly reduce the number of traffic accidents.

The dynamics of features can be included using either the ANN or LSTM model to improve performance when predicting. Additional characteristics including neuronal connection, time-frequency domain elements, and complexity indices [40] may also improve the performance of microsleep prediction.

This study computed the prediction levels using two models and then compared the outcomes. Subsequent research will evaluate multiple models and determine which one is the most accurate by comparing their performances. Furthermore, our goal is to put this system into practice on a hardware platform and assess its effectiveness.

ACKNOWLEDGMENT

The authors would like to acknowledge the great support to Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah for providing research grant, PDU233212 and laboratory facilities to conduct the research.

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