SLEEP STAGES CLASSIFICATION SYSTEM USING DEEP LEARNING

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ABSTRACT

This research presents the design and development of a sleep stages classification system used as an assist tool for physicians who specialize in the Sleep Otolaryngology area, reducing the time and task of sleep stages classification for each time phase. That makes it possible to use the sleep stage analysis results to help diagnose sleep disorders even faster. The system's functionality was divided into four parts: data-preprocessing/data cleaning process, sleep stages training model, sleep stages classification system and graphics user interfaces (GUI) system. This research used a total dataset of 185,915 datasets, divided into 75% training datasets, 15% validation datasets, and 10% testing datasets. The training model process uses three types of signal data from PSG records: Electroencephalograms (EEG), Electrooculograms (EOG), and Electromyograms (EMG). These signals are the key features to creating model used to predict and test performance models. In the GUI system, physicians can import PSG signal logs, and select the type of signal to be displayed. The system will process the data from a file using the model to predict and send the results back to the display page. Users can save prediction reports on devices. In the model performance testing, the F1-Score macro average and F1-Score weight average of the model were 74.1% and 80.63% respectively. Upon examination by a medical professional, it is concluded that the model is practical, and the functional testing of software can work properly.

Keywords: Sleep disorders, Sleep stage classification, Deep learning, Training model, PSG record

1. INTRODUCTION

Currently, there are many diseases caused by sleep disorders such as snoring and obstructive sleep apnea (OSA). There are many patients with this condition, so the diagnosis is very important. In early treatment from Polysomnography (PSG) or Sleeping test, which is a test to diagnose OSA (Obstructive Sleep Apnea). The attending physician must be equipped with various devices to monitor the physiological changes of the body during sleep before being able to diagnose such sleep-related disease. The use of signal data from the PSG record to analyze the sleep stages of each patient or sleep stages classification is one of the important factors that must be used in the diagnosis. The important signal waves used for analysis consist of Electroencephalograms (EEG), Electrooculograms (EOG) and Electromyograms (EMG).

In general, the measurement of the electrocardiogram signal from the patient was completed and analyze the signal for diagnosis will be done by a medical professional directly. From asking a doctor who specializes in otolaryngology and sleep revealed that the problem that doctors had to analyze signals measured from more than ten patients each day. Thus causing a delay and each doctor often interprets the signal differently depending on the doctor’s experience. As a result, most doctors in hospitals turn to use application software package from abroad to help analyze such as Sleepware G3, Profusion Sleep and SleepSign, etc. This software needs to be purchased with a computer or device that measures wavelengths from patients at a very high price. Many hospitals have sleep monitors but no analysis software and there is not enough budget for procurement. In addition, this program still analyzes some signal errors. Most physicians often distrust the analysis results of the program, therefore, they re-examined themselves for accuracy.

From the study to find software as a tool to assist physicians in analyzing the above-mentioned sleep-related signals. This research proposes the design and development of a prototype system for classifying sleep stages by deep learning techniques. To help physicians reduce the time of examination, reduce the workload, and enable the results of the sleep phase analysis in this section, to be used in the diagnosis of sleep-related diseases more quickly.

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2. POLYSOMNOGRAPHY

Polysomnography (PSG) or Sleep studies is a sleep diagnostic test to help for the differential diagnosis of breathing abnormal while sleeping with multiple record variables. PSG recordings include Electroencephalograms (EEG), Electrooculograms (EOG), Electromyograms (EMG), Electrocardiogram (ECG), heart rate and rhythm, chest and abdominal movements, nasal breathing with month and oxygen saturation. In this research, the main signal types that were most commonly used to determine the patient's sleep phase were EEG, EOG and EMG.

Generally, the sleep stages and sleep cycle according to the American Academy of Sleep Medicine (AASM) standards can be divided into five stages: N1 (NREM1), N2 (NREM2), N3 (NREM3) and REM as shown in figure 1.

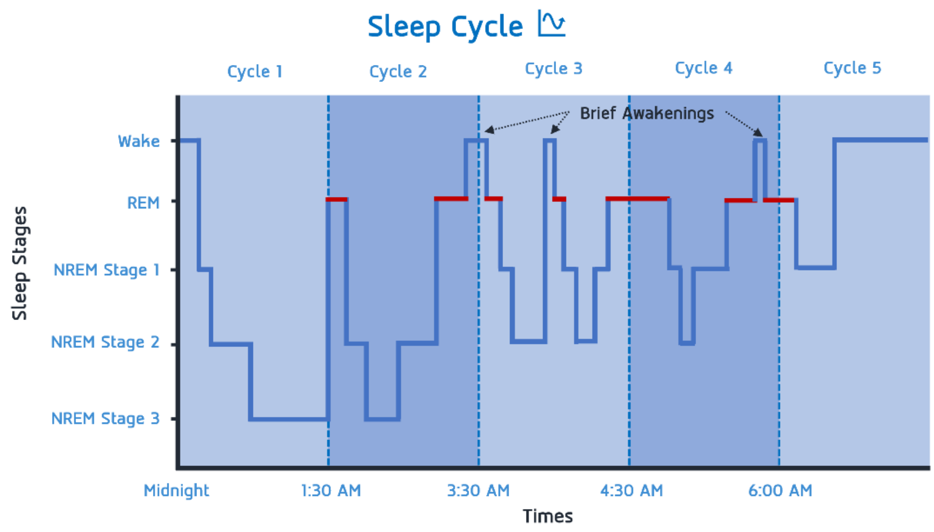

Figure 1. Example of sleep stages and sleep cycle

The sleep cycle is divided into two main phases, REM sleep and NREM sleep. In one night, the average person has about 3-6 sleep cycles, averaging about 4-7 hours of sleep. One sleep cycle is counted from the beginning of REM sleep to the beginning of another REM sleep cycle (excluding brief awakenings or sudden awakenings). Overall, the human body has a complete sleep cycle, approximately 90 to 110 minutes each in the order of N1-> N2 -> N3 -> N2 -> REM. Most of the time, about 75% of sleep is spent in the NREM phase, which each phase of sleep has the properties as following:

1) Wake/Alert is the phase that indicates that you are awake and therefore isn't counted during the sleep cycle. Predominant signal characteristics from EEG signal recording: beta waves and alpha wave are characterized by the highest frequency, lowest amplitude. At the time of awakening, beta wave have a higher influence. They are more pronounced in alpha waves when the person becomes sleepy or relaxed and his eyes are closed.
2) Non-Rapid Eye Movement sleep or NREM can be divided into three phases as follows:

<u>N1 (NREM stage 1)</u> – Light sleep is the beginning of sleep. Generally, it only happens for a short period of 1-5 minutes. During this phase, the brain begins to slow down and breathing is usually at a normal rate. If awakened during this time often don't feel sleepy or may feel that he isn't sleeping. Sometimes there is a slow rolling of the eyes. Some people may experience the phenomenon of shock (Hypnic Jerk), or the feeling of falling from a height and then waking up. Also, some people may hear or see something (Hypnagogic Hallucination). However, sleeping at this stage does not have much effect on the body. This phase typically counts as 5% of the total sleep time. Predominant signal characteristic EEG signal: theta waves are characterized by low amplitude.

<u>N2 (NREM stage 2)</u> – Deeper sleep is transition between the beginning of sleep to the deepest sleep. During this phase, the heart begins to slow down. Body temperature will drop slightly. Usually during this period it takes more than 50% of sleep, which sleep at this stage affects the body both in stimulating short-term memory including

being able to increase concentration. This phase typically accounts for 45% of total sleep time. Predominant signal characteristics from EEG recording: sleep spindles and K complexes. The sleep spindles in the brain wave pattern play an important role in memory consolidation, especially procedural memory and declarative memory. However, the K-complexes are the longest and most pronounced brainwaves. This phase serves to maintain sleep and consolidate memory. It takes about 25 minutes in the first sleep cycle, and it gets longer with each successive cycle.

N3 (NREM stage 3) – Deepest sleep or Slow-wave sleep (SWS) During sleep at this stage, the body begins to be less responsive to external stimuli. It 's the hardest time to wake up. If awakened during this time will feel very dizzy. The body will be in a state of rest as much as possible. It is during which the body repairs and rebuilds tissue and strengthen the immune system and secretion of growth hormone. It is also a period that can cause sleepwalking, nightmares and bedwetting as well. This phase typically accounts for 25% of the total sleep time. However, the time in this sleep phase is less when getting older and will add more in stage N2. Predominant signal characteristics from EEG recording: delta waves which characterized by lowest frequency, highest amplitude.

3) Rapid Eye Movement Sleep or REM Sleep. Sleep during this period is characterized by rapid eye movements. The brain works similarly to when it is awake. There is an uneven level of breathing and muscle movement. During this period, dreaming can occur more than any other sleep phase and usually wakes up spontaneously, so it isn't considered a full sleep phase. This phase of sleep, therefore, contributes to the metabolism in the brain and enhancing imagination. This phase typically accounts for 25% of the total sleep time, usually beginning 90 minutes after the onset of sleep. With each cycle, the cycle begins to grow throughout the night. The first session usually takes about 10 minutes, and the last one can be as long as an hour.

3. SYSTEM DESIGN

The system architecture in this research consists of 4 systems: Data-preprocessing system, Sleep stages model training system, Sleep stages classification system, and Graphics user interfaces system, as shown in figure 2.

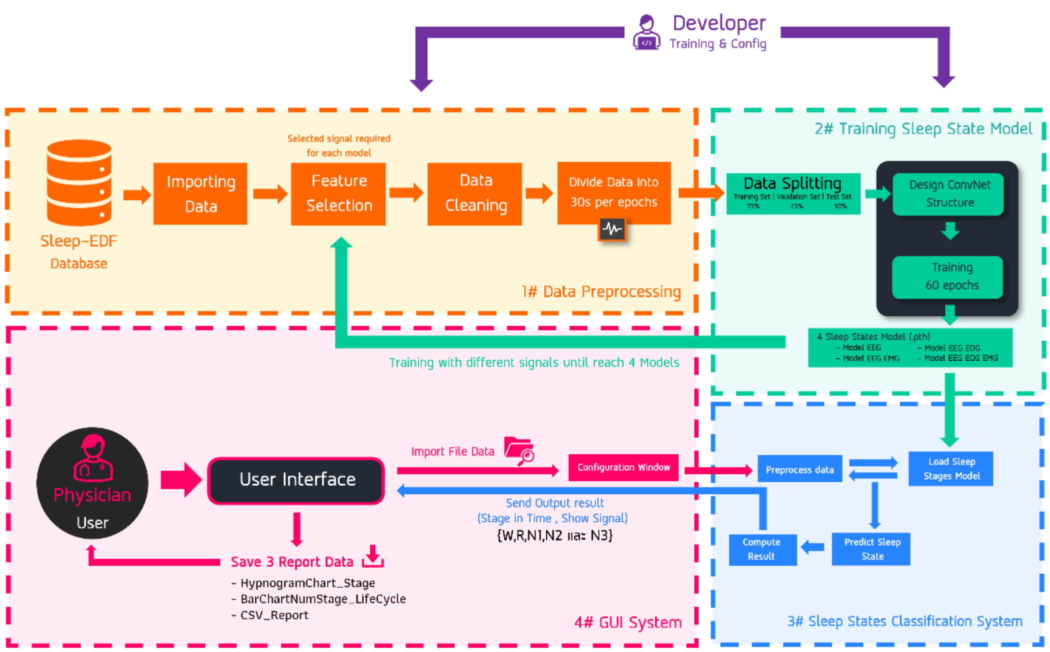

Figure 2. Architecture of Sleep Stages Classification System

The developer uses a dataset that collects signal data from the patient's sleep monitoring record (PSG record) through the Data-preprocessing and data cleaning process. In order to obtain the important features of the desired signal before entering the model training stage. Continue this process until a model is obtained that can recognize the five different sleep stages. On the side of physicians, the system can be accessed through the GUI system. The doctor can import the patient signal data log file with the extension .edf. When user set the display configuration, the system is ready to predict. The system will take the obtained files to separate the internal data for consideration together with the trained model. Then label the data according to the patient's sleep period that during each of these periods, the patient's sleep phase was in any phase and send the result to display to the GUI system.

3.1 Data Pre-processing System

This step involves importing external signal data and taking that data for preliminary manipulation. This process is done to filter and select only signal features that are important for model training. First, a total of 185,915 datasets are imported, each containing two primary reference files: sleep recording file (PSG), which contains the EEG channel (Fpz-Cz and Pz-Oz), EOG horizontal and EMG submental data, and a label section to identify sleep phases, Hypnograms (Sleep patterns), which help the label identifies sleep phases for each period corresponding to the above PSG file. By specifying from the file, it can be divided into 7 classes which are Wake (W), REM, Non-REM stage 1,2,3,4 and ? (Not scored). For the initial filtering, it is necessary to classify a new sleep phase and bring out the necessary internal classes. Due to the large amount of data and insignificant parts for directly categorizing sleep stages.

3.2 Model Training System

This part takes the filtered data and selects the desired signal type to splitting the dataset. Data splitting can be divided into two parts: training dataset of 139,554 sets for bringing data to training the ConvNet model designed and create the desired model, and a dataset for validation of 27,049 sets to track the training process and decide when to stop the training process. The dataset used in the training and validation consist of an input, a signal data, and a label/class indicating the solution.

The model used in this research uses convolutional neural network (ConvNet) as shown in figure 3. It is a deep learning neural network consisting of convolution layer. The layer has the ability to detect local feature on the input, which allows data-training to get a feature extractor suitable for the intended task.

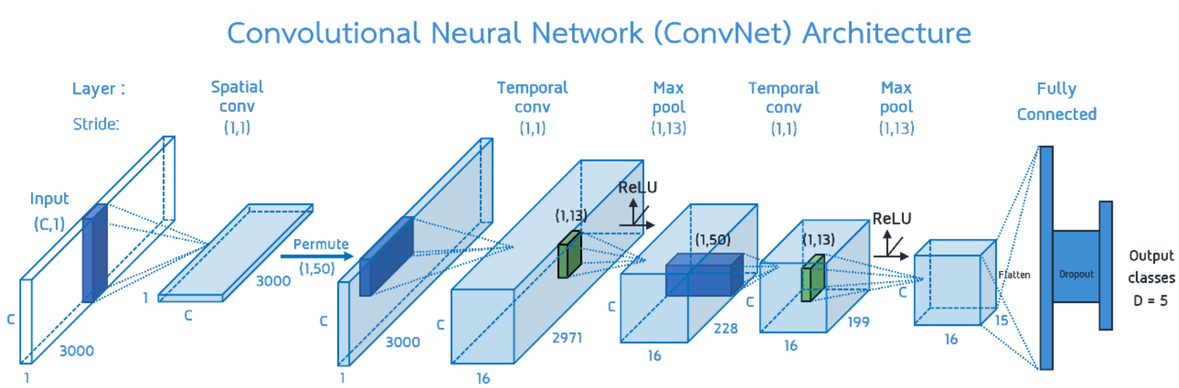

Figure 3. Architecture of Convolutional Neural Network (ConvNet)

As the figure, it can be seen that

- Input on the left is an input window based on the number of channels (represented by C) with intervals of 30 seconds.
- Output layer D (Dense) = 5, on the right is a 5-dimensional vector result, with each dimension mapping to one of the five given classes, which is represented by the results obtained from the sleep stage classification : Stage W, N1, N2, N3 and R.
- Feature extractor in the middle consist of convolutional layer, max pooling (reduces the size of the feature map but retains the features for further use), and nonlinear interface. By defining the activation function using the Rectified Linear Unit (ReLU) function. Until the end, it comes in the form

of a feature map that will be flattened via a flatten layer. This layer is responsible for converting data that is transmitted over multiple channels into a vector form. And it is passed in fully-connected layer until the result (Output) comes out.

Then define the optimizer and loss functions to be used to train the model. In addition, it also indicates that how good or bad was the model at the time? Basically, the training should bring the loss down to the lowest possible value, which will result in better model performance.

- Optimizer, in this research, we use ADAM (Adaptive Gradient Descent Model) is optimization tool for deep neural network.
- Criterion or Loss functions, in this research, Standard Multiclass Cross-Entropy Loss is used.

In the training operation, set the number of train batch size and validation batch size, which is the number of data samples to be fed to the model at one time, to be 128 and 256 respectively. And set the training side to have random data (Shuffle) as well. Then create a loop function to use for training the model by setting the maximum number of rounds of the training interval, known as 'n_epochs', to be 60 total rounds.

Finally, we set the learning rate, a hyperparameter that controls the change in the model's weight in one step of the training model process to 0.001. And set the display during each training session including Training Loss, Validation Loss, Training Performance and Validation Performance. When model training is completed until 60 rounds of training are completed, the trained model is recorded in the '.pth' file extension, the model results are then used in the sleep phase classification system.

3.3 Sleep Stages Classification System

This is a process where a trained model is applied to predict PSG log files that have never been found before. This system works with a GUI for interacting with users as shown in figure 4.

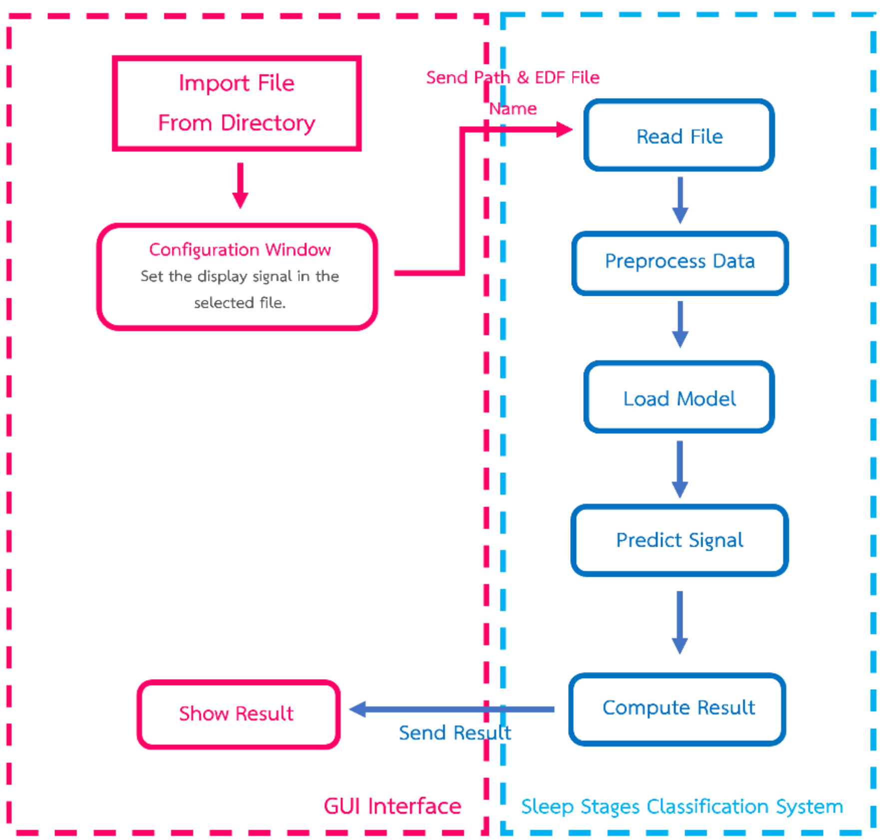

Figure 4. Interoperation between Sleep Stages Classification System and GUI System

In the operation of the GUI after completing the settings. It will take some time to plot the graph, depending on the speed. The time interval and the number of graphs selected are shown in figure 5.

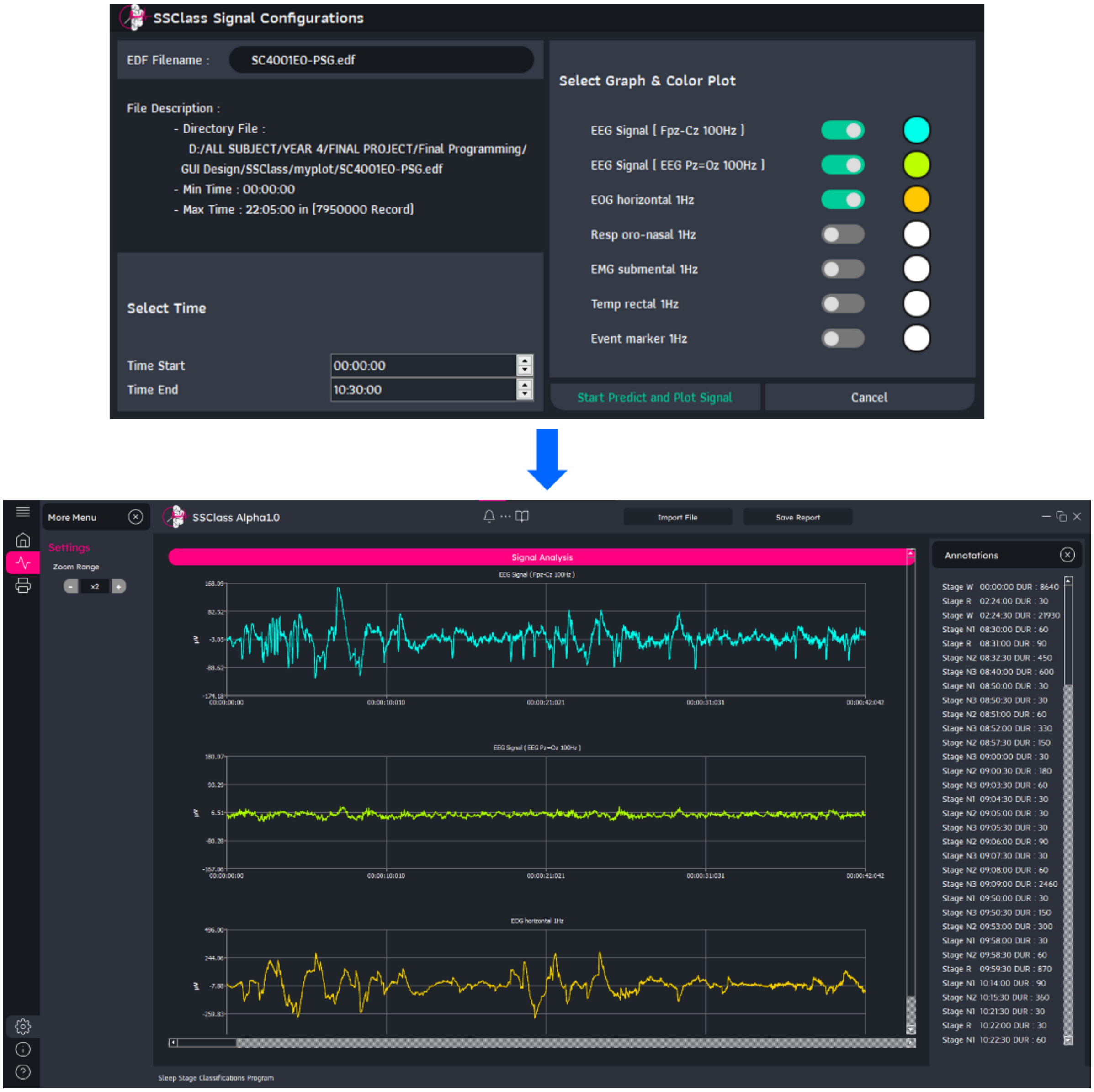

Figure 5. An Example of a Display Based on the Settings on the Configuration Page and Signals Displayed.

When the plot graph is displayed, the selected graph and color will be displayed. Along with the annotations indicators that help direct the sleep stage, including the starting time and DUR:duration that a stage takes place until it changes to the next stage, as shown in figure 5. E.g. Stage N2 08:57:30 DUR: 150 => means that during this time the subject sleeps. The sleep phase has occurred. NREM stage 2 starts at 08:57:30 for a total duration of 150 seconds until the next stage.

After plotting the plot graph in the data analysis tab, users can select tab report to view a summary report of various overviews from the model's predictions as shown in figure 6. This can only be displayed after plotting and predicting the signal. This section will consist of 1) Hypnogram sleep stage in time cycle, bar chart and 2) Number of stage in each time interval (stage per 30-s).

Figure 6. An Example of Tab Report

Hypnogram Sleep Stage in Time Cycle displays the possibility of sleep stage at intervals throughout the recordable file as shown in figure 7. It can be seen that there is an interval of approximately 22 hours for plotting. Stage changes in the same way as the sleep cycle, this section can be used to analyze sleep problems.

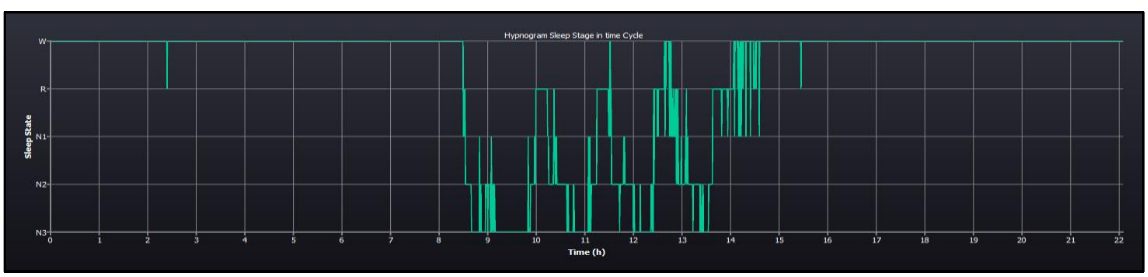

Figure 7. Hypnogram Sleep Stage in Time Cycle

As shown in the figure, what stage of sleep does this person have every 2 hours? For example, the '9-10 hr' box is from line 8 (counting the number 9) to line 10 exactly. If looking at the bar chart – Number of stage in each time interval (stage per 30-s), figure 8. and figure 7. Here, it can be said that from 8:00 AM to 10:00 AM (2 hours interval), there are 5 stage W (30 seconds each) and 46 stage N2.

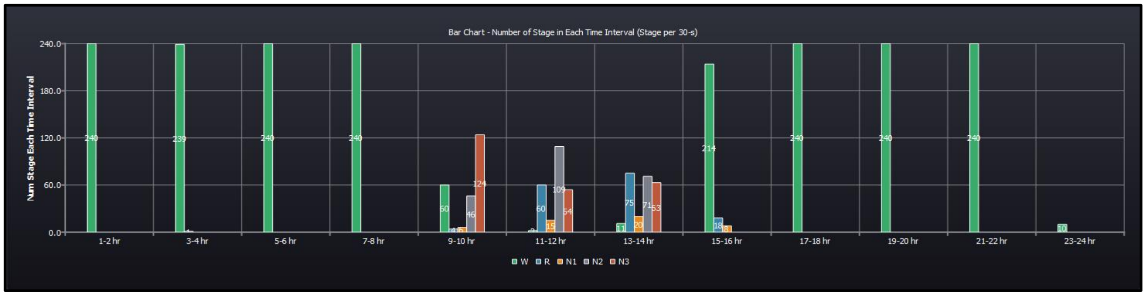

Figure 8. Bar Chart - Number of Stage in Each Time Interval (Stage per 30-s)

4. TEST AND RESULTS

The performance measure focuses on the following model related tests:

4.1 The Learning Performance Test from the Training Model

While training the model, each cycle. Epochs can be configured to show Loss and Accuracy. When training model with training datasets and validation datasets. Where the learning performance of the model is measured by these Loss and Accuracy values. If the Loss value representing the error of the model is less. Shows that the model is well learned. But on the other hand, the higher the Accuracy, the better the model is learned. In general, the higher the number of Epochs training cycles, the Loss decreases and the Accuracy increases to a fixed point.

When training the model is complete, the Loss and Accuracy values from all 60 epochs are plotted to show an overview of the learning that has occurred, resulting in a learning curve. The learning performance of the model from the training and validation dataset is all considered from the point of view of the graph. Where the x-axis of the graph is Epoch and the y-axis is the model efficiency. Model performance was measured after improvements in Weight and Bias were based on dataset used during both training sessions.

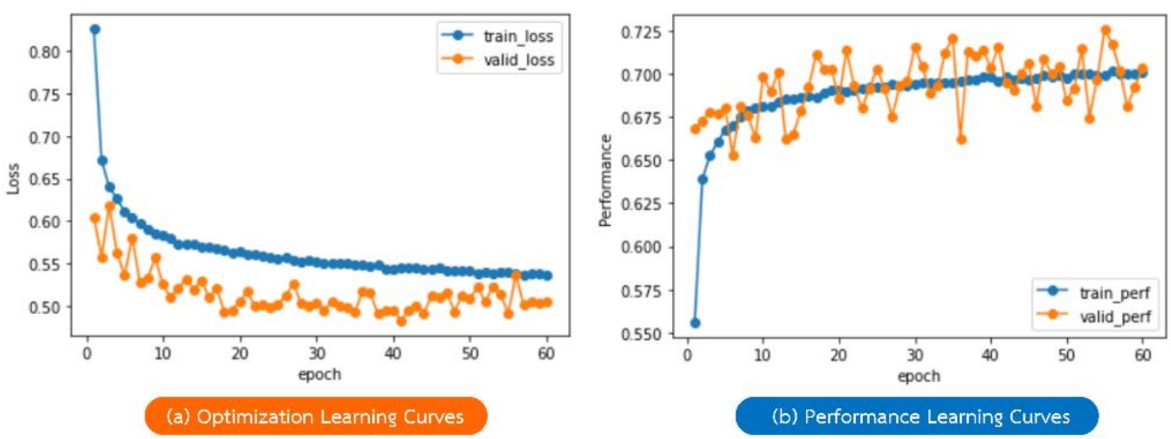

Figure 9. Learning Curve of the Model

As shown in figure 9, it can be seen that the figure on the left is the relationship between Loss and the growing Epochs cycle. (Optimization Learning Curves) and the figure on the right shows the relationship of Accuracy with increasing cycle Epochs (Performance Learning Curves), respectively. Where the blue line is the Accuracy or Loss of the training dataset and the orange line is the Accuracy or Loss of the validation dataset. This graph will help diagnose the model's learning.

4.2 The Performance Test of Predicting the Results from the Testing Dataset

This test measures the performance of the predicted outcomes with the testing dataset until the overall results show the relationship between the actual results and the results that the system can predict through the Confusion Matrix as shown in figure 10.

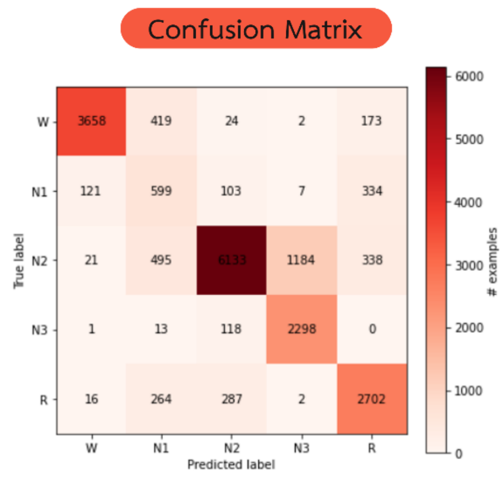

Figure 10. Confusion Matrix of the Trained Model

From the example shown in figure 10. Confusion Matrix of the trained model, it can be explained that the system was able to predict a class Wake (W) result that would match the expected result of 3,658 records out of a total of 4,276 records (obtained from 3,658 + 49 + 24 + 2 + 173). Instead, there are some 419 records predicted to be a class NREM phase 1 (N1) from which it should have been predicted to be class Wake (W).

The numbers with the mentioned Confusion Matrix can be used to calculate the values of True Positive, True Negative, False Positive, and False Negative. And from all the values, we can calculate the performance of predictions with models such as Precision, Recall and F1 Score for each class. When bringing the above Confusion Matrix to display a new result with separate classes that are primarily interested. By calculating True Positive, True Negative, False Positive and False Negative of each class, it can be obtained as shown in figure 11.

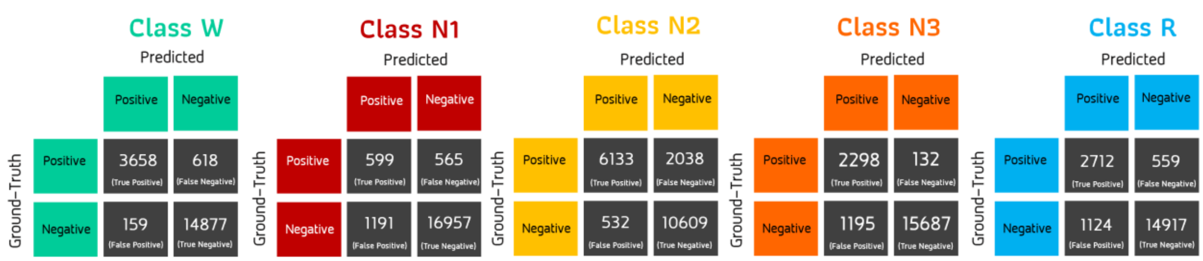

Figure 11. A Separate Model's Confusion Metrix Shows Each Class

It can be seen that all these values can be calculated to assess the effectiveness of model predictions, including Precision, Recall and F1 Score of each class and put them in the summary table as shown in figure 12. Where support is the number of testing datasets supported for that class out of a total of 19,312.

Performance Test

Sleep Stage	precision	recall	F1-score	support
Stage W	0.9583	0.8555	0.9040	4276
Stage N1	0.3346	0.5146	0.4056	1164
Stage N2	0.9202	0.7506	0.8268	8171
Stage N3	0.6579	0.9457	0.7760	2430
Stage R	0.7618	0.8260	0.7926	3271

Figure 12. Total Performance Test Results of the Trained Model

From figure 12. It was found that class stage N1 is the class that the model predicts with the most error and has the least accuracy. On the other hand, class stage W is the class for which the model predicts the most accuracy and precision.

In addition, the Precision, Recall and F1-Score values of each class can be calculated as Macro-Average and Weighted-Average. This is because the number of datasets supported for each class is not the same. Therefore, to compare average performance regardless of the number of datasets vs with regard to

number with weighted average. How much difference will there are? This calculation method is as follows:

Macro-Average is to find the average by focusing on making the results of all classes have equal values.

Regardless of the amount of data available for each class as shown in the equation :

$$Macro\ Avg = \frac{(PERF_{Class\ 1} + PERF_{Class\ 2} + \cdots + PERF_{Class\ N})}{(Number\ of\ Class)}$$

Weighted-Average is an average value that takes into account the number of supported data in each class. By looking at the proportion of data with each class compared to the total data. Therefore, this method is suitable for the imbalanced dataset as shown in the equation:

$$Weight\ Avg = \left(PERF_{Class\ 1} \times \frac{Support_{Class1}}{Support\ all}\right) + \left(PERF_{Class\ 2} \times \frac{Support_{Class2}}{Support\ all}\right) + \cdots + \left(PERF_{Class\ N} \times \frac{Support_{ClassN}}{Support\ all}\right)$$

Where PERF = Performance value for each class

When calculating Precision, Recall, Average F1-Score, including both formats, then bring the plot graph to show the comparison as shown in figure 13.

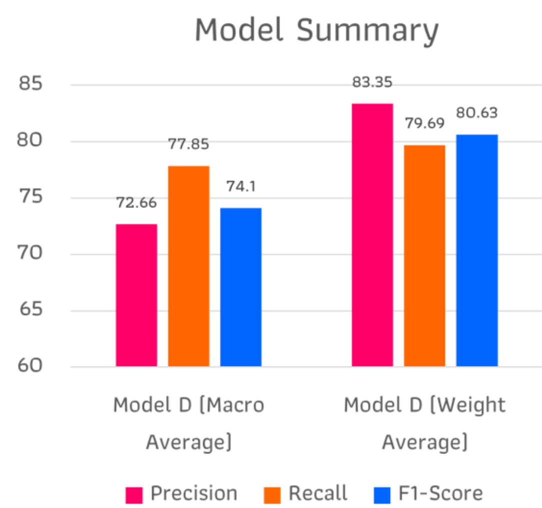

Figure 13. The Average Summary of the model: Macro Average and Weight Average

Finally, if displaying a graph to compare the sample prediction results from the test signal data file for only 1 file (total time 7 hours). The blue line is the true result and the orange line is the result from the prediction as shown in figure 14.

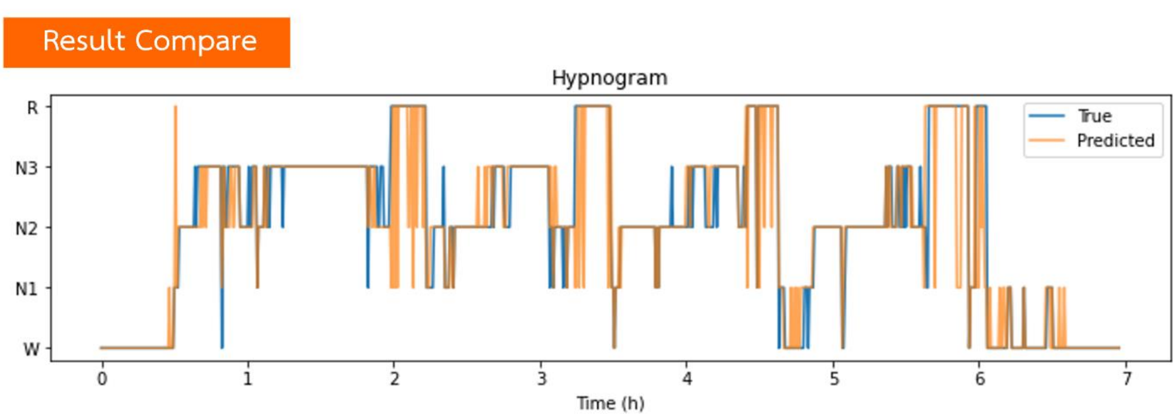

Figure 14. Comparison of the Results from the Prediction using the Model with the Actual Results.

5. DISCUSSION AND CONCLUSIONS

From testing the model's effectiveness in sleep stage classification, it was found that if categorizing efficiency with F1-Score from highest to lowest, we get: Sleep stage W - > Sleep stage N2 - > Sleep stage R - > Sleep stage N3 - > Sleep stage N1.

If we look at the F1-Score Macro Average (which disregards the number of supported datasets in a class makes class equally important) is 74.1%. However, if we look at the F1-Score Weighted Average (taking into account the number of datasets supported in the class, it makes sense to use a weighting method. Since the dataset is of type imbalanced dataset), we get 80.63%.

When considering the learning performance of the model training sessions for each epochs, the performance and optimization learning curves have a graph similar to the good fit learning curve. That is, training loss is continuously decreasing to a constant point, although validation also fluctuates in loss and accuracy, possibly due to the insufficient number of datasets used for verification. This case can be resolved by adding the overall dataset to future training and validation, in order to maintain the original data proportion and also create better performance. And overall, the two graph lines have small gap between them which indicates that the model is well learned. If further improvements were made by adding more datasets, the trained model could be used to predict sleep phases quite accuracy or known as the generalize to new information.

Summary of the results of the experimental use of the application developed in this research, it turns out that the system can work according to the designed function. The system can use a trained model to identify sleep stages with satisfactory performance and work properly as required by a medical professional. Therefore, we can use the system in this research as a prototype system. The system is ready to be put through the ethical process of human research for field testing (β-Test) with signal data from real patients in the future. However, the resulting prediction discrepancy may be due to the fact that the training dataset has a relatively small number of supported data for some classes, and is unbalanced when compared to the doubled support for the class. As a result, the model's learning from training did not recognize the characteristics of such low-volume sleep phases as expected. In the future, the efficiency of the model can be improved by adding a dataset to the training in order to increase the number of support for each class in every possible case.

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