MetaSleepLearner: Fast Adaptation of Bio-signals-Based Sleep Stage Classifier to New Individual Subject Using Meta-Learning

Nannapas Banluesombatkul, Pichayoot Ouppaphan, Pitshaporn Leelaarponp, Payongkit Lakhan, Busarakum Chaitusaney, Nattapon Jaichariyitam, Ekapol Chuangsowanich, Nat Dilokthanakul* and Theerawit Wilaiprasitporn*, Member, IEEE

Abstract—Identifying bio-signals based-sleep stages requires time-consuming and tedious labor of skilled clinicians. Deep learning approaches have been introduced in order to challenge the automatic sleep stage classification conundrum. However, disadvantages can be posed in replacing the clinicians with the automatic system. Thus, we aim to develop a framework, capable of assisting the clinicians and lessening the workload. We proposed the transfer learning framework entitled MetaSleepLearner, using a Model Agnostic Meta-Learning (MAML), in order to transfer the acquired sleep staging knowledge from a large dataset to new individual subject. The capability of MAML was elicited for this task by allowing clinicians to label for a few samples and let the rest be handled by the system. Layer-wise Relevance Propagation (LRP) was also applied to understand the learning course of our approach. In all acquired datasets, in comparison to the conventional approach, MetaSleepLearner achieved a range of 6.15% to 12.12% improvement with statistical difference in the mean of both approaches. The illustration of the model interpretation after the adaptation to each subject also confirmed that the performance was directed towards reasonable learning. MetaSleepLearner outperformed the conventional approach as a result from the fine-tuning using the recordings of both healthy subjects and patients. This is the first paper that investigated a non-conventional pre-training method, MAML, in this task, resulting in a framework for human-machine collaboration in sleep stage classification, easing the burden of the clinicians in labelling the sleep stages through only several epochs rather than an entire recording.

Index Terms—Sleep stage classification, meta-learning, pre-trained EEG, transfer learning, convolutional neural network.

I. INTRODUCTION

In the present day, the technology revolving around healthcare engages in the importance of the quality of sleep for better understanding of different sleep-related disorders such as insomnia and obstructive sleep apnea (OSA) [1], [2]. Furthermore, a fundamental knowledge of sleep staging can be applied to some other novel purposes such as the measuring of an effectiveness of vagus nerve stimulation (VNS) therapy in patients with epilepsy [3] and a development of wearable sleep monitoring devices using in-ear electroencephalography (EEG) [4] or other consumer-grade EEG devices [5].

A conventional method of measuring the sleep stages to assist the diagnosis and the course of treatment involves a combination of different systemic tests as a gold standard sleep study called polysomnography (PSG) conducted in sleep laboratory or medical facility [1], [6]. The sensors are attached to record the electrical signals emitted from different parts of the human body utilizing EEG, electro-oculography (EOG), sub-mental electromyography (EMG), electrocardiography (ECG), airflow, respiratory effort, and pulse oximetry [7], [8]. According to the sleep staging guideline by Rechtschaffen and Kales (R&K), seven stages of sleep include Wake (W), Non-Rapid Eye Movement (NREM consisting of S1, S2, S3, and S4), Rapid Eye Movement (REM), and movement time (MT) [9]. Different observations of the physical events are scored every 30-second epoch in which one of the five sleep stages is assigned and labelled by the clinicians according to the handbook by the American Academy of Sleep Medicine (AASM), comprising five sleep stages (W, REM, and NREM: N1-N3) [10].

In order to classify the sleep stages during a sleep test, clinicians generally examine the EEG recordings as the main signals together with additional imperative signals, such as EOG to distinguish N1 and REM and sub-mental EMG for W, N1 and REM [11]. Due to the possibility of erroneous and subjective labeling of the sleep stages caused by the strains from the scoring and labelling by the clinicians manually through out the whole night sleeping test (approximately 8 hours or 1000 epochs), numerous studies have been proposing automatic sleep stage classification methods including feature engineering with statistical methods, machine learning (ML), and deep learning (DL) approaches.

Different statistical methods, based on the knowledge of sleep staging in the field of sleep medicine, have been developed to extract features from raw signals before feeding them into ML for sleep stage classification [12], [13], [14]. DL approach then has been implemented to extract the features automatically without the requirement of the experts on the domain knowledge. Convolutional Neural Network (CNN) has been utilized to extract different dominant features from the acquired EEG, EOG, and sub-mental EMG signals and placed them into a classifier with fully connected layers [15], [16], [17]. Temporal context has been used to boost the performance by employing the neighboring epochs to the model.

Moreover, one of the more appreciated methods to learn time-series data is to use Long-Short Term Memory (LSTM) [18]. Recently introduced, the state-of-the-art sleep stage classification model entitled DeepSleepNet [19] applies CNN to extract the features and provides them to the LSTM for learning temporal features from a set of successive epochs before feeding them into the classifier. Furthermore, a recently proposed hierarchical Recurrent Neural Network (RNN), called SeqSleepNet, has been compared to DeepSleepNet in terms of performance, establishing a multi-modals evaluation using EEG,
EOG, and sub-mental EMG [20].

Despite the application of the state-of-the-art sleep stage classification models with the capability of DL, numerous amounts of data are required in order to achieve high performance. Moreover, those papers reported the performances of the model from training and testing using the same dataset. However, in a real-world situation, each cohort starts from having only a few samples and may have used different recording systems. The number and the placement of EEG channels, sampling frequencies, experimental protocols, and types of subject may lead to data variation and the alteration in the performance of the classification model [7], [21]. Therefore, it is difficult to ensure the achieved high accuracy of the selected models from newly established datasets or devices.

II. MOTIVATION AND CONTRIBUTION

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According to aforementioned limitations of the existing DL approaches, one solution for the limited number of samples problem, vastly applied in computer vision area, is transfer learning (TL) methodology. The model is pre-trained by a huge dataset, followed by the application to the new in-coming dataset [21]. Further elaborations are described in Subsection III-A.

In our previous work, we have shown that the TL methodology is possible to apply to EEG data [22]. The performance of event-related potential (ERP) classification tasks could be improved by pre-training the model from other datasets. Recently, researchers have also begun to employ TL method for sleep stage classification. Some methods were applied directly from the image classification models [23]. However, the features learned by the model of interest, which has been pre-trained for image classification (two-dimensional, 2D), are not similar to those pre-trained using the bio-signals (one-dimensional, 1D) in sleep stage classification [24]. Despite the large sleep datasets (with permission required), such as Montreal Archive of Sleep Studies (MASS) [25] dataset, are available, they were not employed for pre-training the model. This can be beneficial in TL to other newly established datasets to be pre-trained and fine-tuned using the same task.

Various TL approaches using sleep datasets have been implemented to achieve the best performance. Phan et al. [26] proposed a cross channels and cross modalities TL approach using the aforementioned SeqSleepNet model architecture. The model was pre-trained using the EEG signals from a huge dataset, followed by the fine-tuning on a smaller dataset consisting of either different EEG channels or horizontal EOG. Different fine-tuning paradigms were explored, including no fine-tuning, partial, and whole network fine-tuning, which was demonstrated to be the best paradigm [20]. Using different datasets, Andreotti et al. [21] fed the pre-trained model with more diverse subjects, i.e., both healthy and pathological subjects as well as examined on various model architectures. The aim of the fine-tuning was also changed to personalize to each subject. However, almost all subjects in the fine-tuning dataset were required to train in both studies. Therefore, in the real-world application, when analyzing data of a new cohort, clinicians still need to annotate the sleep stages for many recordings. Successively, Phan et al. [27] extended their previous works by also investigating in a suitable number of subjects for the fine-tuning phase. The problem in selecting the most suitable subjects to be representatives (to be trained) is imperative as the conditions of each dataset might be differed, e.g., age ranges, types of sleep disordered. In addition, not only different types of cohorts, devices, or EEG electrode placements resulted in diverged recorded signals, various subjects or recording sessions can also impact the variability [28]. Therefore, even if the model is fine-tuned with some subjects from particular cohorts, the model cannot be ensured that it will work efficiently in every incoming subject.

In this work, we aimed to propose a new framework called MetaSleepLearner, in which instead of replacing the human labor for sleep staging, we motivate and encourage the collaboration between clinicians and machines. For every incoming subject in any cohorts, the system is able to mitigate the time-consuming problem by letting the clinicians label for several samples instead of a whole night, while the rest will be done by the system. To accomplish our goal, an advanced TL method called Model Agnostic Meta-Learning (MAML) [29], which has been widely used in images, but to our best knowledge, has never been used in sleep stage classification, were applied in our approach. While all previous works focused on the performance in each state-of-the-art network or different fine-tuning paradigms, we instead attempted to elicit the performance of MAML in which its capability includes pre-training on various tasks and is claimed to be an algorithm with fast adaptation to the new tasks by using only a few samples. Therefore, we illustrated a method to adapt the MAML to this task which is related to the information of the inputs and the variability of the data. Additionally, the comparison between TL with the conventional pre-training method and MAML were mainly investigated.

III. METHOD

A. Transfer Learning in Deep Learning

Many DL researchers and practitioners do not have enough computational resources or sufficient data to train DL models from scratch. It has been found to be more practical to adapt existing models, which are shared in the community, to the task at hand. This practice, namely Transfer Learning (TL), has become very influential in many fields such as robotics [30], [31], computer visions [32], [33], and natural language processing [34], [35], [36]. The open-sourced codes and models are normally trained on different tasks or different datasets. Therefore, they might not be readily usable for a task of interest. TL methods describe heuristics of how to consolidate knowledge from one task and unpack it in other learning tasks. TL has been used with three major components of DL algorithm: (i) the pre-trained weights [32], [33], (ii) the network architecture [37], and (iii) the learning algorithm and optimization [38]. These components influence the learning by biasing the model in different ways. For example, neural network’s weights can put the neural network model close to a certain area in the optimization landscape, encouraging the learning to converge at a certain local minima.

B. Model Agnostic Meta-Learning

In this work, we focused on a method of TL via pre-trained weights called Model Agnostic Meta-Learning (MAML) [29]. MAML describes an algorithm that learns a set of pre-trained weights, which can be easily adapted to new tasks. The benefits of MAML go beyond the reuse of features because, while consolidating, MAML considers the possible changes in these features in the adaptation phase. In
other words, MAML grasps (in pre-training phase) at how to quickly learn or adapt in related tasks. We call this ability of learning to learn — meta-learning.

This meta-learning ability of MAML is interesting because, unlike image data, the useful features of the bio-signals are less understood. While it is easy to reuse the primitives in image data, it is unclear how to reuse the features from one person (or one device) can be reused, without adaptation, for another person (or another device).

Formally, a neural network $f_\theta$ parameterized by $\theta$ performs well on a set of tasks $T_{b}$, $b \in \{0, \ldots, B\}$. In other words, it finds $\theta_b$ such that the sum of the evaluations, after updated, to be as low as possible. Therefore, $\theta_0$ has to be easily adaptable, i.e., it has to be easily updated into a set of good $\theta_b$.

The main hypothesis assumes that $\theta_0$ will be able to be generalized to other tasks $T_{\text{new}}$, which are from the same distribution as $T_{1}, T_{2}, \ldots, T_B$. Therefore, by training $f_\theta$ on a set of related tasks, we consolidated the knowledge of these tasks into $\theta_0$, which could be easily adapted (or fine-tuned) to an unseen task.

C. MetaSleepLearner

The benefits of MAML were employed to our fast adaptation procedure, entitled MetaSleepLearner. The overall process consists of two phases is illustrated in Figure 1. The input data included different channels of bipolar EEG, EOG, and submental EMG, which are described in Appendix I. Due to the variability of bio-signals in each subject mentioned in section II, each recording of the subject represented one meta-task (referred as $T_b$). The meta-training was performed by transferring the knowledge from the pre-training phase ($\theta_0$) to fine-tune a subject from other cohorts. The model ($\theta''_b$) initialized by $\theta_0$ from the pre-training phase is then fine-tuned using the training set and tuned hyperparameters with the validation set. Ultimately, the performance of $\theta''_b$ is evaluated using the test set, concluding the ability of the fine-tuning phase to be used with any subject with altered conditions.

1) Pre-train (Meta-training): The model was first pre-trained using 3 subsets of MASS [25] (SS1, SS3, and SS5) as the training sets and SS4 as a validation set. Each subject in each subset was treated as one meta-task ($T_b$), in which the tasks were divided into two groups: for training ($T_{\text{train}}$) and for validation ($T_{\text{val}}$). The model weights, referred to as meta-weights ($\theta_0$), were first initialized to the random weights. In each meta-training iteration, as described in Algorithm 1 and illustrated in Figure 5 (Appendix II), 9 $T_b$ ($T_1, T_2, \ldots, T_9 \in T_{\text{train}}$) were randomly selected (3 tasks per MASS subset, each containing the data recorded from the three modalities). In order to adapt to those selected tasks, each $T_b$ copied the weights from $\theta_0$ as its own fast-weights ($\theta'_b$):

$$\theta'_b \leftarrow \theta_0,$$

(1)

Subsequently, two sets of samples were randomly selected from $T_{\text{train}}$, referred to as $D_p$ and $D_q$, in which each set consisting of $K$ epochs per stage, i.e., the variable number of samples per stage. Thus, a total $K \times 5$ epochs were chosen per set. The adaptation to those tasks was performed separately. For $num$ updates steps, each step starting from using $D_p$ to update the $\theta'_b$ was shown as follows:

$$\theta''_b \leftarrow \theta'_b - \alpha \nabla_{\theta''_b} \mathcal{L}_{T_b}(f_{\theta''_b}^T)$$

(2)

where, $\alpha$ is an updating step size or learning rate ($update_{Ir}$), $D_q$ was used for calculating the $\mathcal{L}_{T_b}$ which would eventually be kept in $\mathcal{L}_{T_{\text{val}}}$. After all 9 selected meta-tasks were executed, the summation of losses were calculated as:

$$\mathcal{L}_{\text{meta}}(\theta_0) = \sum_{b=1}^{B} \mathcal{L}_{T_b}(f_{\theta''_b}^T),$$

(3)

which is the objective function that MAML was trained to mini-
mize. As a result of a succession of meta-training iteration, $\theta_0$ was updated with the gradient descent of $L_{meta}$ using

$$\theta_0 \leftarrow \theta_0 - \gamma \nabla_{\theta_0} L_{meta}(\theta_0).$$

where $\gamma$ is the learning rate of updating meta-weights ($meta_{lr}$).

Following the re-calculation of $\theta_0$, the meta-validation was performed by sampling the tasks from $T_{val}$. The sequence procedures abided by the process of meta-training and for tuning the hyperparameters, e.g., number of iterations. This meta-validation procedure benefits the pre-training process for fast adaptation because the $\theta_0$ is not selected when it immediately performs well with the validation set, but it is selected when it achieve good validation loss after adapting to that data, resulting in the effectiveness for adaptation

2) Fine-tune (Adaptation): The knowledge from pre-training phase was transferred to this phase by initializing the fine-tuned weights, abbreviated as $\theta''$, with $\theta_0$, for fast adaptation to new individuals in the new cohorts, referred as $T_{new}$. A subject was selected at a time from either Sleep-EDFx [40], [41], CAP [42], [43], ISRUC [44], and UCD [45] in which the data were recorded from EEG, EOG, and sub-mental EMG. The samples of sleep epochs extracted from the selected subject were randomly divided into three different sets: a set of $K$ samples/stage as a training set, another set of $K$ samples/stage for validation, and the remaining samples for testing. The adaptation procedure was similar to the adaptation in meta-training. The gradient descent was performed to adapt the $\theta''$ to each individual with only those $K$ epochs per stage in training set. The $\theta''$ was then validated against the other $K$ epochs per stage from validation set in order to find the suitable hyperparameters. Ultimately, the performance of our model was examined using the remaining epochs, segregated from the other two sets of $K$ epochs per stage from the subject with the updated $\theta''$.}

IV. Experiments

In this section, we described the experimental setups which aimed to achieve several goals. Firstly, we tried to show the improvement of TL compared to training the model from scratch. Secondly, the results from using only EEG signals and multi-modals (EEG, EOG, sub-mental EMG) in TL were shown. Thirdly, the efficiency of our pre-training approach were compared against the conventional approach by using several datasets including both healthy subjects and patients. Lastly, the model interpretation were illustrated to investigate the knowledge the model acquired from our approach. In all experiments, the procedure was divided into 2 steps: pre-training and fine-tuning. The simplified version of CNN networks were used, as described in Subsection A.

A. Model Specification

Based on the practicality that the MAML could be applied to any networks with gradient-based learning, we applied the state-of-the-art model, namely DeepSleepNet [19], which used raw signals as inputs in our approach. In order to reduce the computational time and resources, our model was designed in a much simpler edition. The model composed of two stacks of CNN layers: small filters and large filters. Both filtered were then concatenated and fed into a Softmax layer for classification. More details of model architecture are described in Appendix III.

B. Pre-training

Pre-training is the first step of TL. As mentioned earlier in Subsection III-C, for each meta-task $T_b$, referring to each subject, two sets of data were randomly selected for meta-training. Each set included $K$ epochs per stage. The subjects, whose recorded stages were less than $K \times 2$ epochs, were filtered out. To satisfy our goal which allows the clinicians to label only several samples during a PSG, reducing the strain, the $K$ was set as 10. After filtering the number of epochs per stage, there were 30, 37, and 24 subjects from MASS SS1, SS3, and SS5, respectively, as parts of the training set. For validation, to be comparable with number of meta-training tasks, 9 subjects with sufficient number of recorded epochs per stage were randomly selected from MASS SS4 and fixed as the representatives in every model run. MASS was selected for the pre-training due to its large amount of data compared to the other datasets. In basic PSG and all acquired cohorts, C3 is one of the most commonly used EEG electrode placements, in accordance with the International 1020 system. Hence, the bipolar C3-A2 EEG electrodes were chosen as samples along with EOG and sub-mental EMG provided by each subset. In order to examine the performance of our proposed method, the pre-training phase was executed in an identical network architecture with two different paradigms.

1) Proposed Approach: The meta-training procedures are described in Subsection III-C. The model was meta-trained until the trend of meta-validation loss increased and the model’s weights (meta-weights) were kept at the best iteration as $\theta_0$. The set of hyperparameters included the learning rate at the updating meta-weights ($meta_{lr}$ $(\gamma)$ $\in \{10^{-2}, 10^{-3}, 10^{-4}\}$), the learning rate inside the sub-task adaptation ($update_{lr}$ $(\alpha)$ $\in \{10^{-2}, 10^{-3}, 10^{-4}\}$), and the number of updating steps ($num_{updates}$ $\in \{5, 10, 15\}$).

2) Conventional Approach: Generally, the training procedure involves all samples in the training datasets as they are pooled towards one place. At first, the model was performed on the original sets of data (non-oversampling). However, to avoid the class-imbalanced issue, the training data were over-sampled by duplicating them to achieve an equal number of epochs per stage instead. The validation loss was found to be lower in comparison to the non-oversampling sets. In each iteration, the model randomly drew upon the samples to train using mini batches, performing the gradient descent in the same network architecture as our approach. In order to have
the same number as the proposed approach, $K \times 2$ or 20 epochs per stage from each subject were randomly selected for validation. The model was trained repeatedly until the validation loss did not improve for at least 200 epochs. The best iteration was maintained as $\theta_0$. The sets of hyperparameters included the $\text{learning\_rate} \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$, and $\text{batch\_size} \in \{250, 350, 450\}$. It was deemed logical to use this set of $\text{batch\_size}$ in order to equalize it to our proposed approach by arranging $K \times 9$ per stage $= 450$. Additionally, the number multiplying to $K$ was also varied as $K \times 5 = 250$ and $K \times 7 = 350$.

In each pre-training paradigm, all combinations of hyperparameters were performed. Afterwards, the set returning the lowest validation loss was selected. The model was performed 5 times with the hyperparameters, rising 5 sets of $\theta_0$ from our approach and 5 sets of $\theta_0$ from conventional pre-training.

C. Fine-Tuning

The knowledge from the first phase was then transferred to the fine-tuning phase for adaptation to new individuals in new cohorts. To fine-tune the model, three types of weights initialization for comparison of the methods were used: 1) $\theta_0$ from our approach, 2) $\theta_0$ from conventional pre-training and 3) random initialization using Xavier [39]. Each model was fine-tuned to each individual subject from the unseen datasets including Sleep-EDFx, CAP, ISRUC, UCD and the remaining subset from MASS (SS2), composing of both healthy subjects (as reported in their datasets) and patients.

Since $K$ epochs per stage were also required for training and validation in this phase while remaining samples were required from each subject for the testing in the fine-tuning phase, the subjects with less than $K \times 3$ epochs per stage were filtered out from the experiments. The EEG electrodes were used differently including C3-A2 from ISRUC, UCD and MASS SS2, C3-P3 from CAP, and Fpz-Cz from Sleep-EDFx. In the fine-tuning phase, the validation set was used to select the most suitable $\text{learning\_rate} \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$, as well as the number of training iterations. The default $K$ and maximum training iterations were set to 5 and 500, respectively. However, in some cases, the recordings from patients required more training samples and iterations. Therefore, the $K$ was extended to 10 and the maximum number of training iterations was set to 1000. In order to demonstrate that the model could be applied to an actual arbitrary situation, e.g., the random selection of any epochs labelled by the clinicians, the model was performed 5 times per indicated subject and per weight initialization. Moreover, the random samples in each run were divided separately. For the comparison between the performances of all pre-training paradigms, the samples which were randomly picked during the same round were identical to the previous run.

D. Model Interpretation using Layer-wise Relevance Propagation (LRP)

By applying the proposed fast adaptation procedure, the pre-trained model was adapted to the new incoming subject, i.e., $T_{new}$, in the fine-tuning phase. The fine-tuning and the validation were performed using only 5-10 epochs per stage. Regardless of the performance, it is necessary to assess whether the method of learning is reasonable. Hence, the application of the Layer-wise Relevance Propagation (LRP) was used for examination. LRP describes a model interpretation method, allowing the reasons for making each decision to be seen, i.e., prediction. It was employed in the previous work to interpret the classification model using the EEG signals [46]. In this study, LRP was employed, revealing the conception of the reasons that model used for each prediction. Initializing from the fine-tuned model ($\theta^f$), LRP propagates backward from the output ($f_{out}$) throughout all the layers, reaching the input layer. The $\text{Relevance}$ scores ($R_i$) was returned, which was found to be devised from the same shape as the input of the original model (3000, 1, 3). Each value of $R$ indicates the reason behind the contribution of each sampling point from the signals to the decision of the model. The $R$ scores was computed as:

$$R_i = \sum_j a_{ij} w_{ij},$$

where $R_i$ is a $R$ of neuron $i$, $i$ and $j$ are two neurons of any consecutive layers, $a_{ij}$ is an activation of neuron $i$, and $w_{ij}$ is the trained weight (parameter) connecting between neurons $i$ and $j$.

V. RESULTS

The results elaborated in this section are divided into two parts. Subsection A describes the suitable hyperparameters and achieved loss values from both conventional and our proposed pre-training procedures. In Subsection B to E, the evaluation of the performance after fine-tuning (adapting) to new individuals in the new cohorts are reported, as shown in Table I. The number of acquired subjects, including those that remained after filtering with the sufficient number of epochs per stage and excluding the recordings that could not be used or the unprovided selected EEG channels, are displayed in Appendix II. The performance of each experiment was reported as macro F1-Score $\pm$ standard errors (MF1 $\pm$ SE).

A. Pre-training

In this Subsection, we investigated the trends of pre-training loss from both conventional approach and our proposed approach. In the conventional pre-training method, $\text{learning\_rate} = 10^{-2}$ with $\text{batch\_size} = 450$ epochs are generally the best set of hyperparameters, giving the lowest validation loss. The Figure 2 (a) displays an example of the results using the conventional pre-training method. The model was fitted after training for 1,317 iterations with validation loss $= 0.75$. From all 5 runs, the validation loss achieved ranged from 0.66 to 0.75. In comparison, using our approach, the best validation loss was achieved from $\text{meta\_lr} = 10^{-3}$, $\text{update\_lr} = 10^{-2}$, and $\text{num\_updates} = 10$. However, the results were not much sensitive to these exact values of the learning rates. As shown in Figure 2 (b), the best validation loss achieved was 0.46 at iteration of 14,912. As a result from the 5 runs, the validation loss ranged from 0.46 to 0.52. The meta-validation procedure, defining whether the weights are suitable for adapting, instigated lower validation loss in comparison to using the conventional method, when the loss was achieved once the adaptation reached 10 steps. It was deemed usual as our approach required larger amount of iterations due to the fluctuating loss from the meta-training procedure. Since the models weights were updated separately from the 9 meta-tasks before updating the meta-weights in every iteration, the direction of the gradients was more variable. However, both loss values and number of pre-training iterations did not affect the practical usage as the approach could utilize the $\theta_0$ from this phase to adapt to the data from the new incoming cohorts in the fine-tuning phase.

B. Advantages of Transfer Learning

Prior to inspecting the improvement of the proposed pre-training procedures, we examined whether the network trained using TL performed better than the neural network training from scratch. In this experiment, only EEG signals were used. CNN was then changed
The results are averaged from all 5 pre-trained weights per each paradigm and 5 runs per each weight. ± yielded only 18 approximate MF1 of 50, the model without the pre-training phase tunings using our approach and conventional approach yielded an performed in a total of 5 runs. As shown in Table I, while the fine-tune the models, initializing from the three paradigms: our proposed Sleep-EDFx dataset, consisting of healthy subjects, were used to fine-tune 1D CNN and the input shape was (3000, 1). The recordings from Sleep-EDFx dataset, consisting of healthy subjects, were used to fine-tune the models, initializing from the three paradigms: our proposed approach, conventional approach, and the model without pre-training (randomly initialized using Xavier [39]), in which each of them was performed in a total of 5 runs. As shown in Table I, while the fine-tunings using our approach and conventional approach yielded an approximate MF1 of 50, the model without the pre-training phase (not displayed in the Table I) yielded only 18 ± 0.002. In addition, no F1-score higher than 26 was yielded from any sleep stage. The model did not achieve well performance with only several samples, i.e., $K = 5$ epochs per stage without any pre-trained knowledge. This confirmed that the Deep Neural Networks would require the training with a large amount of data in order to achieve high performance. Furthermore, the TL paradigm could become one of the solutions for the issue of small available data.

### C. Effects of input information on MetaSleepLearner performance

We hypothesized that the information of inputs might affect both performances of TL and capability elicitation of our approach. The performances in the fine-tuning phase using EEG signals were compared against using EEG, EOG, and sub-mental EMG as inputs. The data from Sleep-EDFx (SC) were used in this experiment. When using only EEG signals, the calculated MF1 reached only 51.91 ± 0.006 and 52.89 ± 0.006 for the conventional approach and our approach, respectively. To compare against the three modals as inputs, the network was changed to 2D CNN. The MF1 yielded from each paradigm was computed to be increased to 63.87 ± 0.007 from the conventional approach and 68.34 ± 0.006 from our approach, in which the bio-signals were from the same set of subjects within the same cohorts in only EEG condition. It is well acknowledged to conclude that EOG and sub-mental EMG are necessary for the sleep stage classification, similarly to the routine performed by clinicians. The higher MF1 within our approach suggests the necessity in using all three modals in performing the sleep stage classification and the elicitation of the performance of our approach to outperform the conventional approach ($p < 0.05$).

### Table I: Performance after fine-tuning on each individual in each cohort using $K$ epochs/stage.

| Dataset          | K | EEG only                  | W | N1 | N2 | N3 | REM | MF1  |
|------------------|---|---------------------------|---|----|----|----|-----|------|
|                  |   | conv                      | ours | conv | ours | conv | ours | conv | ours | conv | ours | conv | ours | conv | ours | conv | ours | conv | ours |
| Non-patients     |   |                           |     |     |     |     |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| EEG only         | 5 | 59.47                     | 60.46 | 56.15 | 57.16 | 16.71 | 16.55 | 66.70 | 67.09 | 67.29 | 70.21 | 52.72 | 53.44 | 51.91 | 52.89 |
| EEG, EOG, Sub-mental EMG |   |                           |     |     |     |     |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| Sleep-EDFx(SC)   | 5 | 69.94                     | 74.32 | 72.37 | 76.77 | 31.78 | 36.56 | 75.21 | 79.20 | 74.24 | 78.94 | 65.75 | 70.22 | 63.87 | 68.34 |
| ISRUC (Subgroup 3) | 5 | 69.75                     | 73.89 | 72.60 | 80.32 | 43.64 | 47.71 | 65.55 | 70.33 | 81.26 | 83.31 | 69.28 | 72.18 | 66.67 | 70.77 |
| CAP              | 5 | 68.42                     | 74.03 | 50.87 | 64.84 | 17.08 | 20.84 | 73.39 | 78.25 | 76.37 | 80.40 | 67.54 | 74.74 | 75.05 | 63.81 |
| MASS (SS2)       | 5 | 70.87                     | 76.39 | 62.90 | 71.19 | 24.71 | 29.17 | 76.06 | 80.81 | 74.07 | 78.37 | 71.56 | 76.93 | 61.86 | 67.29 |
| Patients         |   |                           |     |     |     |     |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| EEG, EOG, Sub-mental EMG |   |                           |     |     |     |     |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ISRUC(Subgroup 1) | 5 | 63.75                     | 68.74 | 67.79 | 74.77 | 40.02 | 42.73 | 58.46 | 64.43 | 73.03 | 77.11 | 64.63 | 68.47 | 60.79 | 65.50 |
| Sleep-EDFx(ST)   | 10| 58.26                     | 65.41 | 53.09 | 57.56 | 23.74 | 29.32 | 63.27 | 71.85 | 70.87 | 78.12 | 49.70 | 55.38 | 52.13 | 58.45 |
| UCD              | 10| 51.43                     | 56.59 | 48.00 | 53.87 | 24.91 | 27.11 | 49.84 | 59.41 | 68.53 | 72.65 | 33.81 | 38.90 | 45.02 | 50.39 |
| CAP (Patients)   | 10| 70.34                     | 75.09 | 69.37 | 76.14 | 29.59 | 34.10 | 69.35 | 72.37 | 78.25 | 80.81 | 70.82 | 77.32 | 63.76 | 68.74 |

The bold numbers represent the higher performance with significant difference ($p < 0.05$). The results are averaged from all 5 pre-trained weights per each paradigm and 5 runs per each weight.

(conv = conventional approach, ours = our approach)
D. Adaptability of MetaSleepLearner in different kinds of subjects

Considering the advantages of MAML, the higher performance of fast adaptation in every dataset was expected to be found from using our approach compared to the conventional approach. Examples of the validation loss during the fine-tuning phase are illustrated in Figure 3. Four subjects were selected for the illustration from different cohorts including both healthy subjects and patients. Only the first 100 iterations were shown, although the model was trained until fitted to the data. In Figure 3, the middle line is the mean of the 5 runs from the selected subjects and the areas with colors represent the standard deviations (SD). In most of the results, after fine-tuning for a few iterations, the loss from our approach could be noticeably observed as lower than the conventional approach.

In a deep inspection of the results, the subjects who were labelled as healthy from the ISRUC dataset (Subgroup 3) with the same EEG electrode placements as the pre-training phase, i.e., C3-A2, were first explored for fine-tuning of the networks. The average MF1 using our approach reached 70.77 ± 0.008 while using the conventional method yielded only 66.67 ± 0.008. The percentage of improvement using our approach was 6.15%, revealing the significant difference (p < 0.05) in the mean of both approaches. The second dataset to be explored was CAP despite containing the data with different EEG reference channel from the MASS dataset used in pre-training. Our approach was found to statistically outperform the conventional approach with 11.85% of MF1 improvement, yielding 63.81 ± 0.005 for our approach and 57.05 ± 0.007 for the conventional approach. Subsequently, MASS SS2, which was not employed in the pre-training phase, was used in the fine-tuning. The enhanced adaptation of our approach (8.77% of improvement) implied the benefit of fine-tuning the data of the subjects whose recordings are similar to the data used in the pre-training phase. Our approach yielded 67.29 ± 0.007 while the conventional approach produced 61.86 ± 0.008. The last dataset, as reported in Subsection V-C, was Sleep-EDFx (SC), showing that the usage of different EEG electrode placements could also be fast adapted with our approach with the improvement of 7.14%. Further details of the results from confusion matrix and hypnogram are elaborated in Appendix V.

To determine whether our approach could be applied to a simulation of a real-world setting, the data of patients with different ratio of each stage and bio-signal characteristics from the control group were used in fine-tuning. Four datasets were chosen to examine the performance of the models adaptation. The results from using the ISRUC (Subgroup 1) dataset showed that the MF1 obtained from both pre-training paradigms was reduced compared to the control groups. Our approach achieved 65.5 ± 0.01 while the conventional approach attained 60.79 ± 0.011. The approach also statistically outperformed the conventional method with 7.74% improvement. The other cohorts (Sleep-EDFx (ST), CAP and UCD) were also tested. However, the model performed mostly low score in both approaches, i.e., the average MF1 was less than 50. To elucidate the depleted execution, K was increased to 10 epochs per stage, requiring the increase in maximum training iteration to 1,000. Despite the reduction in performance using Sleep-EDFx (ST), with the similar number of subjects to Sleep-SDFx (SC), yielding 58.45 ± 0.006 and 52.13 ± 0.005 by our approach and the conventional approach, respectively, our paradigm performed significantly progressing with the improvement of 12.12%. Additionally, the results from the inputs from CAP dataset confirmed the increase by our approach (68.74 ± 0.005) with 7.81% improvement, outperforming the conventional approach (63.76 ± 0.006). It is important to note that many recordings from the patients in the CAP dataset did not contain the C3 EEG electrode channel and some of the data were not valid. Albeit the differences in bio-signal conditions, the experiments were performed on patients with various disorders including nocturnal frontal lobe epilepsy (17), REM behavior disorder (3), periodic leg movements (1), narcolepsy (1), insomnia (1), and bruxism (1). The final dataset used in the experiment was UCD, achieving the lowest performance. Although our approach reached only 50.39 ± 0.01, the improvement from the conventional approach (45.02 ± 0.01) rose up to 11.92%.

Inclusively, using the three modals from the recordings of both healthy subjects and patients, our approach outperformed the conventional pre-training method with significant differences (p < 0.05) in overall accuracy, MF1, and F1-score in every sleep stage. This implied that our proposed pre-training paradigm could enhance the performance of TL for fast adaptation to the new individuals in new cohorts.

E. Model Interpretation

In order to understand what the model learns from our approach, the evaluation by LRP was inspected, as displayed in Figure 4. Three samples per stage recorded from two subjects in the Sleep-EDFx (SC) dataset were selected as examples. The size of the LRP results were the same as the original inputs shape (30 seconds length × 100 sampling frequency), while the colors represented the level of effects to each prediction by the model, i.e., R scores from LRP. R scores were scaled with all three modals in each sample. The blue to red colors signified the lowest to highest contribution of the prediction. Only the correct prediction samples were explored in order to determine whether the performance of the model was sufficient with correct learning method. Figure 4 displays the predictions from W, N1, N2, N3/N4, and REM stages. According to the red colored sampling points at the left most column figures, EOG signals were found to have an impact on the prediction of W stage. This conformed with the practical views in which the EOG signals would generally show higher activity in the W stage compared to the other stages during the sleep interval. In N1 and REM stages, the similar portions of the three bio-signals were highlighted. This implied the necessity of the three modals to assess the correct classification. In clinical settings, clinicians routinely identify these stages using all three modals. EOG signals can be observed to distinguish between N1 and REM with those with higher activity as REM [11]. Similarly, the information obtained from the decrease in sub-mental EMG signals can distinguish N1 from W stage. Furthermore, for stage N2, the model emphasized on the EEG signals, especially the area denoted with the characteristics of K-complex and sleep spindle which are the main EEG traits of this stage. The model also paid attention to only the EEG signals in identifying N3/N4 stage, in which the entire samplings in each epoch were analyzed. In accordance to its name “Slow Wave Sleep, referring to the EEG signals with low frequency, the model required the information of the signal frequency to predict this sleep stage. To do that, the model would require the entire sample length as illustrated with the non-dark-blue color in the visualization of the EEG modal. From all above visualization results, it verifies that using only several epochs to fine-tune the model is possible for the adaptation of the model to new individuals in new cohorts as the networks are capable of learning with reasonable predictions and acceptable directions.

VI. Discussion

One of the objectives of this study is to explore the ability of the proposed novel pre-training method to enhance the TL approach used in sleep stage classification. Although our model was modified into a humbler version which could not be in comparison to the
larger state-of-the-art classification methods, to our best knowledge, this is the first study using this task to explore a novel method of pre-training without challenging the whole process performed by the state-of-the-art models previously. Not as an alternative machinery to replace clinicians, we offer and encourage a procedure to consolidate the human-machine collaboration system for sleep stage classification with an attempt to reduce the workload and ameliorate the time-consuming task of manually labelling the sleep stages. Using the Model Agnostic Meta-Learning or MAML [29], our approach lessens the burden of the clinicians during a sleep test, labelling only 5 or 10 epochs per sleep stage in preference to one whole night while allowing the machine to handle the rest of the samples.

A. Performance evaluation

The results confirmed the success of our approach, outperforming the simplified version of the conventional pre-training method in both healthy subjects and patients when the bio-signals are present with EEG, EOG, and sub-mental EMG, which are recorded generally in the medical PSG. One explanation for the achievement of the model could be attributed to the meta-learning which minimizes the losses across all meta-tasks ($T_k$) after the adaptation of each task. The impact generalized the meta-weights, or $\theta_0$, while prompting them to become more adaptable to new tasks or new individuals from newly introduced cohorts with only several samples. In contrast to the conventional pre-training approach, the model tried to minimize the loss from all samples, making the model more fitted to the training data. To support these statements, some examples of fine-tuning results which used healthy (Sleep-EDFx (SC) & ISRUC) and patients (Sleep-EDFx (ST) & CAP) cohorts are shown in Figure 3. Even we selected the results from only four subjects to show in this figure, it can be found mostly in the results that during the first iteration where fine-tuning was not performed, the $\theta_0$ obtained from our approach acquired a very high loss, which was much higher than using $\theta_0$ from the conventional approach. However, after fine-tuning was performed for only a few iterations, our proposed procedure could fast adapt to the provided data, resulting in much better and eventually higher quality performances as reported in Table I. Nevertheless, the amount of knowledge provided for the model needs to be adequate for learning, i.e., all three modalities are required in order for all the procedures to perform acceptably.

B. Adjustment of schematic frameworks

In particular, further adjustments could be explored in order to improve the effectiveness of the proposed method. Firstly, the precision rate of the evaluation of sleep stage classification could be increased. The prediction of the stages N1 and REM were shown to be lower than the other stages. One reason might be due to the lower amount of N1 epochs compared to the others. However, this is to be expected as they were in accordance to the general EEG characteristics of both stages. Moreover, in the dataset consisting of the recordings from patients, the performance of every stage exhibited a decrease in accuracy. When examining the hypnogram, it is interesting to note that the surrounding epochs might affect the decision and assist in improving the performance. It could be speculated that some of the predictions could be improved when the information regarding the preceding or the succeeding epochs are presented to the model. Similarly, higher accuracy might be stemmed from an input longer than 30 seconds. Hence, the one-to-many or many-to-one training frameworks from the previous works might affect the balancing of the transitioning stages [16], [17]. Secondly, extending the ability of the networks would unquestionably enhance the classification. In this study, we extracted a modified version of simple CNN networks, imitating from DeepSleepNet [19] and maintaining the capability to assume any gradient-based networks. Therefore, the state-of-the-art networks such as DeepSleepNet, SeqSleepNet, or other larger networks could be applied to our proposed TL procedure. Nevertheless, the limitation of MAML involves the requirement of a large amount of computational resources due to the second-order derivation. Thus, the newer method editions, such as iMAML [47] and Reptile [48], might assist in evaluation of the larger networks. Although the performance of those methods might not highly outperform the original MAML, these latest methods require lower amount of resource to operate.

C. Hyperparameters assessment

Both pre-training and fine-tuning are the two imperative phases in our methods, where some parameters can be tuned for an improvement. One of them is the $K$ variable, representing the number of training samples per stage. In the pre-training phase, $K$ was set as 10, whereas in the fine-tuning phase, $K$ was set as 5 and 10 alternatively. Although these numbers were chosen in order to regulate the labelling of the samples in a new subject, it should be considered in future works as the alterable $K$ affects the performance of the model. The $num\_updates$, the number of updating rounds inside each meta-task during meta-training, is also one of the parameters of interest, affecting the performance of the model. In this study, the performances of the model alternating between using 5, 10, and 15 rounds, measured by the validation loss during the pre-training...
process, exhibited similarities among each other. However, in some conditions, 15 rounds resulted in a higher validation loss than the other rounds. One could speculate that the higher the number of training rounds, the more general interpretation of the knowledge and the further distance from the best parameters of each meta-task ($\theta_\mu$) could be achieved. Ultimately, although the result suggests that the most optimal number of updates for the most fitted validation loss from the three values we selected is 10 rounds, higher or lower values of num_updates could still be further explored.

D. Benefits from actual practicality and future works

In order to drive further impact stemmed from our objective of enhancing the human-machine collaboration, it is advantageous for the model to guide the clinicians of which epochs should be labelled, leading to an effective fine-tuning of the model. One approach that could be implemented to enhance the predictive performance is called active learning [49]. It points out which samples, i.e., epochs, benefit the model, in which low confidence in prediction might be exhibited, and presents them to the clinicians to provide their expertise and label the samples efficiently.

An alternative way to use learning feedback for improvement is to perform model interpretation. Any improvements will be valuable if the model presents the results and learns in the most possible factual way. Since it is challenging to comprehend the learning contents of the deep neural networks despite the application of TL, an effectual feedback system is crucial to review the results. The utilization of Layer-wise Relevance Propagation or LRP ensures that the decisions generated by the models stemmed from the same reason the clinicians might use for annotation. One possibility involves the performance metrics showing that the prediction of N1 could be mistakenly classified as REM and vice versa. The visualization states for the reason that it is not only because of the similarity in the characteristics of EEG signals, but also the ways the model learns in both classes. However, our results suggest that the model did not learn to make a reasonably decision in some patients, leading to a lower quality performance in the patients on comparison to the healthy controls. Therefore, the concern over the interpretation of any models along with the adjustment of the other networks or training procedures should be investigated to ensure the precision of the improvement.

The filtering of the subjects with insufficient samples per stage also affected the learning ability of the model. Albeit a low number of filtered out subjects, it implies data manipulation, requiring a necessity to search for a new solution in order to serve in an actual PSG. In terms of the bio-signal data, only EEG channels selected in this study were bipolar electrodes, commonly used in all datasets. It would be beneficial to explore other various EEG channels from the selected datasets, allowing an extensive usage of data in the new cohorts. In addition, the pre-training procedures can be improved by feeding more datasets to facilitate the learning of the pre-trained models from subjects with different demographic and clinical backgrounds. Despite its advantage, data variation from different cohorts may complicate the model processing. Thus, a deep inspection is essential. Moreover, the data from an actual clinical oriented recording (non-public) may have proven important for data diversity. Currently, our team at the Vidyasirimedhi Institute of Science & Technology (VISTEC) in collaboration with the Center of Excellence in Sleep Disorders, King Chulalongkorn Memorial Hospital, Bangkok. Thailand, has been establishing a partnership, aiming to assemble and collect various sleep data in patients during an actual PSG for future development of sleep lab technology.

VII. Conclusion

This study proposed a fast adaptation method, using a Model Agnostic Meta-Learning (MAML) approach, in order to transfer the acquired sleep staging knowledge from a large dataset to new individuals in new cohorts. A simplified edition of the CNN network was pre-trained using our approach with MASS dataset, followed by the adaptation or the fine-tuning to each new subject from other cohorts, including Sleep-EDFdx, CAP, ISRUC, and UCD, by using only several samples from each subject. The performance was compared against the pre-training of the conventional approach. The investigation using only EEG signals confirmed that only one modal of recordings contained insufficient knowledge for sleep stage classification and elicitation of our approach performance. Subsequently, three bio-signal modal (EEG, EOG and sub-mental EMG) were employed. Both our approach and the conventional approach achieved higher performance. Moreover, our approach statistically outperformed the conventional approach as a result from the 5 runs of fine-tuning using the recordings of both healthy subjects and patients. The study also illustrated the learning of the model after the adaptation to each subject, ensuring that the performance was directed towards reasonable learning. This indicates a framework for human-machine collaboration for sleep stage classification, easing the burden of the clinicians in labelling the sleep stages through only several epochs rather than an entire recording.

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APPENDIX I

Five publicly datasets were used to evaluate our method. The detailed summary of these five datasets is displayed in Table II. The number of subjects used in each dataset is explained in the section V. The study was approved by Rayong Hospital Research Ethics Committee (RYH REC No.E008/2562), Thailand.

A. Montreal Archive of Sleep Studies (MASS)

MASS is a collection of a total of 200 polysomnograms from 97 male and 103 female subjects [25]. The cohort was split into five subsets (SS1-SS5), according to the research protocols used when collecting the data. These recordings were manually classified by sleep experts using AASM guidelines with 30-second epoch length for SS1 and SS3 and R&K rules with 20-second epoch length for SS2, SS4, and SS5. The labels following the classification by R&K comprised eight classes, namely sleep stages W, S1, S2, S3, S4, REM, and MT, with those that are unable to be classified labelled as “UNKNOWN” [9], [17]. In this study, the AASM guidelines with five sleep stages were followed instead for consistency, merging sleep stages S3 and S4 into a single sleep stage and the segments of MT and “UNKNOWN” were removed. Furthermore, the EEG and EOG recordings were pre-processed with a notch filter of 60 Hz and band-pass filters of 0.3 - 35 Hz. All recordings from the original sampling frequency of 256 Hz were downsampled to 100 Hz. All segments were generated into 30-second long, extending both ends by 5 seconds for segments that were originally 20-second long.

B. Sleep-EDFx

The Sleep-EDFx dataset contains two sets of data from two studies: the effects of age on sleep in healthy controls (SC) and the effects of temazepam, a benzodiazepine, on sleep in subjects with difficulty falling asleep (ST). The number of subjects from SC and ST are 20 and 22, respectively. These recordings had a sampling rate of 100 Hz and were classified according to R&K rules, which were merged into five stages following the AASM standard to be consistent with MASS. Due to the long periods of W stage at the beginning and at the end on most of the recordings, the methods were modified following the methods used in Supratak et al. [19] by truncating the awake periods at each end to at most 30 minutes. In addition, most subjects contain two-night recorded signals, but only the data obtained during the first night from each subject were used in our experiment.

C. CAP Sleep Database

The title of the Cyclic Alternating Pattern (CAP) Sleep Database is originated from the recurring EEG activity at intervals during NREM, where its irregularity may imply a range of sleep disorders. The database consists of 108 PSG recordings including 16 recordings from healthy subjects and 92 pathological recordings, which were categorized into nocturnal frontal lobe epilepsy (40), REM behavior disorder (22), periodic leg movements (10), insomnia (9), narcolepsy (5), sleep-disordered breathing (4), and bruxism (2). The stages were scored by expert neurologists according to the R&K rules [41], but also modified according to the AASM standard, similar to the other datasets.

D. ISRUC

A total of 118 PSG recordings, named ISRUC-Sleep dataset, was introduced in 2015 by a team at the Sleep Medicine Centre of the Hospital of Coimbra University (CHUC). The dataset includes three separated subgroups of PSG signals from 100 subjects with history of sleep disorders recorded on one data acquisition session, 8 subjects recorded on two different sessions and two different dates, and 10 healthy subjects. However, only subgroup 1 and 3 were used in our experiment. The sleep stage classification followed the five stages according to the AASM, labelled by two human experts in each session.

E. St. Vincent’s University Hospital / University College Dublin Sleep Apnea Database (UCD)

Revised in 2011, the St. Vincent’s University Hospital / University College Dublin Sleep Apnea Database, abbreviated as UCD, holds the overnight PSG of 25 subjects (21 male and 4 female) with diagnoses of possible sleep-related breathing disorders such as OSA, central sleep apnea, and snoring. Sleep stages were scored by sleep experts, following the R&K rules, into 8 stages: W, N1, N2, N3, N4, REM, Artifact, and Indeterminate. Similar to other datasets, S3 and S4 were merged into one stage in order to comply with AASM standard and the segments Artifact and Indeterminate were removed in this study. The recordings were pre-processed with a notch filter of 60 Hz, followed by the downsampling from the original sampling frequency of 128 Hz to 100 Hz for consistency with the other datasets. The W periods at the beginning and at the end of each recording which were longer than 30 minutes were trimmed to approximately 30 minutes on both ends.

APPENDIX II

The meta-training procedure, which is described in Subsection III-C, could be illustrated as follows:

APPENDIX III

The model, shown in Figure 6, designed in a simpler version of DeepSleepNet, composes of two stacks of CNN layers: small filters (the left/pink stack) and large filters (the right/blue stack), in order to capture the temporal and frequency information, respectively. Each CNN layer is followed by the relu activation function [50]. The l2 regularization is used in the first CNN layers as the original network, in order to prevent the over-fitting of noises and artifacts from the signals. However, all CNN layers were changed from 1D to 2D, resembling the study by Phan et al. [27] to support multi-modal signals.
### TABLE II: Number of total subjects, number of subjects used, number of 30-second epochs for each sleep stage, channels used, and bandpass filter (if any) applied for each dataset

| Dataset                  | # total subjects | # used subjects | Number of 30-second epochs | EEG channels | Bandpass filter |
|--------------------------|------------------|-----------------|----------------------------|--------------|-----------------|
|                         |                  |                 | W  | N1   | N2   | N3/N4 | REM | Total   |
| MASS (SS1)               | 47               | 30              | 6734| 3675 | 12473| 3008  | 3608| 29462   |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
| Sleep-EDFx (SC)          | 20               | 18              | 3168| 1162 | 8027 | 2846  | 3391| 18594   |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
| ISRUC (subgroup 1)       | 100              | 16              | 3252| 1879 | 4438 | 2837  | 2126| 14532   |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
| ISRUC (subgroup 3)       | 10               | 10              | 1817| 1248 | 2678 | 2035  | 1111| 8889    |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
|                         |                  |                 |    |      |      |       |     |         |
| UCD                     | 25               | 19              | 3334| 2414 | 5338 | 2388  | 2291| 15765   |

For the input data, as described in Appendix I, only MASS dataset was bandpass filtered with the proper frequency range in order to use as a pre-training data. For other cohorts, all signals were notch-filtered with either 50 or 60 Hz, depending on the datasets and re-sampled data to reach 100 Hz sampling frequency (if necessary), without any further pre-processing. We assumed that the procedure could handle the raw data from different hardware devices along with different pre-processing methods such as hardware filters.

Fig. 6: Example of sleep stage classification network, demonstrating the performance of our proposed fast adaptation procedure. 1 epoch (1 input sample) contains 30 seconds of EEG, EOG, and sub-mental EMG signals. The conv blocks refer to the CNN layers, each with a variety of filter size, number of filters, and stride size, respectively. The bold numbers in the first conv blocks of each side represent the small (left) and large (right) filters of the CNN layers.

The performance of our method was assessed after the adaptation (fine-tuning phase). In each $T_{new}$, after the $\theta''$ fitted on its training data, the model with the set of hyperparameters achieving the lowest validation loss was used for the evaluation. All remaining epochs from that subject were employed as the test samples. The performance was reported in overall accuracy and macro F1-Score (MF1),

$$\text{Overall Accuracy} = \frac{\text{no. of correct prediction}}{\text{total number of samples}}$$

MF1 was computed by averaging the F1-score from all classes. The F1-score per class was computed from precision and recall of its class where $TP = \text{True positive}$, $FP = \text{False positive}$, $TN = \text{True negative}$ and $FN = \text{False negative}$,

$$\text{F1-score} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$
APPENDIX V

![Confusion Matrix](image)

**Fig. 7**: Examples of confusion matrix after the fine-tuning from pre-trained weights of the proposed approach (left), the conventional approach (center), and the differences between both results (right) using (a) Sleep-EDFx (SC - Healthy Subjects) and (b) Sleep-EDFx (ST - Patients). The results are the summation from all subjects and all runs.

![Hypnogram](image)

**Fig. 8**: The hypnogram displaying the comparison between the labelling by clinician and the model’s prediction of a representative subject from Sleep-EDFx (SC).