

Automated CAP Phase Detection in EEG for Sleep Disorder Analysis using Deep Learning

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ABSTRACT

Cognitive, physiological and human health effects are the main consequences of sleep instability and neurological sleep disorders. The Cyclic Alternating Pattern (CAP) has been identified as a valuable biomarker in assessing the sleep instability during the Non-Rapid Eye Movement (NREM) sequence. This research formulates an automated CAP phase classification framework based on Continuous Wavelet Transform (CWT) and Lightweight Convolutional Neural Network (CNN). Pre-processing of raw EEG recordings obtained from the CAP Sleep Database is conducted through band-pass filtering to eliminate noise and unwanted artifacts. In a bid to extract transient CAP-related features, the preprocessed EEG data segments are converted into time-frequency representations by Continuous Wavelet Transform (CWT), with each EEG segment being transformed into a two-dimensional scalogram plot/image. These scalogram representations are then fed into the Lightweight CNN model for automated classification of the CAP subtypes. The proposed framework integrates the time-frequency signal analysis with feature extraction using deep learning methods to enhance the CAP phase recognition results. For the experimental evaluation, Accuracy, Precision, Recall, F1-Score and the Confusion Matrix analysis were used. However, the proposed system attained a classification accuracy of 93.8% while preserving a computationally frugal architectural form that can be employed for pragmatic clinical analyses. Therefore, the development framework indicates automation of sleep microstructure assessment and ascertain a probable approach of EEG based sleep instability detection.

Keywords: Cyclic Alternating Pattern, Continuous Wavelet Transform, Lightweight CNN, Deep Learning.

I. INTRODUCTION

Sleep has fundamental role to keep neurologically balanced and regulates cardiovascular and metabolic homeostasis and consolidate memories and physiologically stable. The sleep architecture disturbance has significant correlations with number of neurologically and psychologically based diseases, such as insomnia, sleep apnea, epilepsy, depression and neurodegenerative diseases [1]. In the past few years, sleep microstructure analysis became an important research area in biomedical signal processing because of its clinical importance in understanding the sleep instability and abnormal brain states. Among all the physiological signals used for sleep analysis, Cyclic Alternating Pattern (CAP) is the one of the most robust biomarkers for detecting the sleep instability of the Non-Rapid Eye Movement (NREM) sleep [2]. The pattern of the CAP consists of repetitively occurring a series of transient activation (A-phases) and background (B-phases) activities in the EEG signals. A-phases have 3 subdivisions A1, A2 and A3 depending on

the synchronization characteristics and the EEG activation pattern. Detection of accurate CAP phase classification plays a great role in diagnosis of sleep fragmentation, neurological disorders and pathological sleep.

Conventional CAP analysis relies on the visual inspection performed by the sleep experts to analyze long-term polysomnographic data, although this approach is considered clinically acceptable, but it is computationally inefficient, labor-intensive and involves considerable inter-observer variability [3]. With the explosion of huge volume of sleep data, it is no longer feasible for humans to perform the manual annotation of all the CAP signals. Hence, it is crucial to design a computationally feasible CAP detection system. EEG signals are non-linear and non-stationary. So, the feature extraction of EEG is a very difficult task. The standard time-domain and frequency-domain approaches could not effectively extract the transient EEG variations occurring in the CAP events [47, 53, 55]. Time-frequency methods like Continuous

Wavelet Transform (CWT) have received a lot of attention due to their efficiency in joint analysis of time and frequency information of the signals [4]. The CWT representation has the capacity to retain more localized EEG variations compared to standard spectral analysis methods and produce the information-rich features for automated classification systems. In recent years, the Deep Learning techniques have made excellent success in biomedical signal processing and EEG classification automation. The CNN, Transfer Learning models and transformer-based vision model achieve high accuracy in Hierarchical image feature extraction [5-8, 25, 36, 50]. But most of the deep learning model has very high computational costs, large memory requirement and more parameters that make them less feasible to be utilized on real-time environment and on the devices with limited computing power [9-11, 15-18]. For clinical applications on wearable devices, artificial intelligence at the edge needs to be optimized. Designing deep learning models in this aspect is a considerable task. There must be a system to run on low power devices while maintaining high detection accuracy. There is an unaddressed gap in using classification accuracy as only parameter to define the efficiency of the detection system and there is lack of models capable of being run on edge.

This paper introduces an efficient Light-weight CNN based framework for automated CAP subtype classification integrated with CWT for EEG time-frequency analysis. The proposed method represents EEG signal into scalogram image and feeds it to the computationally efficient CNN architecture for the CAP subtypes.

The major contributions of the paper are:

1. To propose a lightweight DL framework which detects multi-class CAP subtype for achieving joint optimization of classification accuracy and computational efficiency.
2. The module for localized time-frequency representation using CWT has been designed in order to achieve efficient extraction of non-stationary EEG transients than standard spectral methods.
3. An edge-aware approach has been utilized in designing the DL model so that it can support real-time detection on low-resource clinical monitoring devices.
4. Extensive performance evaluation on clinical data for different sleep disorders demonstrates high diagnostic accuracy with low latency at the output.

The rest of the paper is organized as follows:

- Section 2 presents the related work,
- Section 3 presents the proposed work,
- Section 4 presents the model architecture,
- Section 5 presents the results and performance analysis followed by conclusion.

II. RELATED WORK

Automatic sleep analysis and classification of CAP phase have considerably gained performance with recent development in the Deep Learning and biomedical signal processing domains [1-5, 8, 9]. With respect to traditional machine learning techniques, the deep learning methods exhibit an improved ability to learn the hierarchical features directly from the raw EEG data and the time-frequency representation of signals. They can efficiently extract the nonlinear and transient patterns of EEG, which are related to neurological activation and sleep instability [6, 14, 15]. The Convolutional Neural Network architectures have proven to be effective for the EEG-based sleep classification and CAP detection, since they can automatically learn the discriminative spatial features from biomedical signal representations [8, 10, 15]. Early deep CNN architectures like VGGNet, ResNet, and DenseNet reported some promising classification accuracy on the biomedical image processing problems. However, their complexity and enormous number of parameters are often associated with high computational load and long training time [14, 15]. Such models can be too complex and are thus unsuitable for real-time health care systems where computational resources and time are limited [6, 14]. Therefore, Lightweight Deep learning models were proposed in recent literature in order to mitigate this limitation of high computational load and parameter complexity while achieving acceptable classification performance [14, 15]. Lightweight CNN architectures are often based on optimized convolution operations, small filter dimensions, and efficient feature extraction strategies making it well-suited for the low-resource and edge-based healthcare applications.

A recent study shows that light-weight models drastically improve computational efficiency with minimal reduction in classification accuracy [8, 14]. In recent times, hybrid deep learning models that integrates the wavelet transform into light-weight CNN architectures show considerable performance improvement for automatic EEG analysis and CAP detection applications [10, 11]. Time-frequency representation analysis plays an important role in EEG signal interpretation since the EEG data are typically nonlinear and non-stationary in nature [11, 12, 13]. The conventional Fourier based spectral

analysis approaches are not sufficient for localizing transient EEG dynamics and its characteristics associated with the CAP events and sleep instability [11, 13]. Continuous Wavelet Transform has shown to be the most effective time-frequency representation method for biomedical signal processing due to its excellent ability to simultaneously localize temporal and spectral events [11, 12, 13]. These wavelet-based approaches extract transient patterns present in the EEG data and boost discriminative feature extraction for automatic sleep classification systems [10, 12]. A lot of recent literature has explored generation of wavelet-based scalogram followed by application on CNN networks for EEG classification [10, 11, 12]. In these methods, the EEG signals are transformed into time-frequency distribution representations, which can be directly utilized for CNN in order to extract the spatial features of the EEG data [10, 15]. The research reports state that the wavelet based scalograms greatly increase CAP detection performance as compared to the hand-crafted features-based approaches [8, 10]. However, in these systems, it has been observed that most of the reported systems do not address the issue of dataset imbalance, thereby suffering from the insufficient representation of the minority class [8, 9].

Attention mechanisms and transformer-based architectures are receiving enormous attention for EEG based signal processing tasks [6, 14]. Vision Transformer and attention enhanced CNN models exhibit good ability to model the long-range feature dependency, thus improving the contextual representations of EEG data [6, 14]. The hybrid models combining CNN and transformer architecture have presented significant improvements in automated CAP classification tasks [6].

Explainable Artificial Intelligence approaches like Grad-CAM, SHAP and LIME have gained an increasing amount of research attention to make the biomedical deep learning models more interpretable and transparent [16, 17, 18]. They can visually illustrate important segments of EEG signals that have affected the models' decisions and hence would significantly build confidence during automated medical diagnosis [16]. In spite of offering interpretability, these explainable models are applied as post-hoc visualizations without integrating the explainability factor into the model optimization and feature extraction processes [16, 17]. Hence, they cannot fully assure trust and reliability of the decisions made by the model in healthcare scenarios.

The following major research gaps are identified from the literature:

1. Current strategies are largely dependent on manually constructed feature extraction algorithms, constraining flexibility and generalization capabilities.
2. Traditional spectral analysis algorithms have shown limitations in capturing EEG variations related to CAPs.
3. Many neural networks exhibit computational complexity with numerous parameters, hindering practicality.
4. Trust Class imbalances among CAP data sets have a notable impact on subclass predictions.
5. Lightweight deep learning models for clinical applications have received little consideration.
6. Existing algorithms display lower levels of robustness for heterogeneous sleep pathologies.

The proposed Lightweight CNN based CAP Classification framework is designed to balance classification accuracy, time-frequency feature localization, and energy efficiency by incorporating CWT as a direct component of the feature extraction stage. This process results in an accurate, computationally efficient, and robust model tailored to the resource-limited real-time, on-device clinical sleep monitoring.

III. PROPOSED WORK

This study introduces a new automated classification framework of CAP phase based on CWT combined with Lightweight CNN for rapid analysis of sleep instability in EEG signals. Traditional methods of CAP scoring suffer from high computation complexity, low ability of transient features' expression and lower generalization in non-stationary EEG analysis. The proposed model transforms 1-D EEG to 2-D time-frequency scalogram image using CWT, which then is fed into a lightweight CNN for CAP subtype classification, effectively detecting transient EEG activations correlated to different CAP stages with time-frequency localizations, while maintaining computationally low architecture for clinical application with resource restriction. develop a new automatic CAP phase classification method by using Continuous Wavelet Transform (CWT) and Lightweight Convolutional Neural Network (CNN) for automatic sleep instability analysis from EEG signals. The new proposed framework intends to alleviate the issues that conventional CAP scoring systems encountered including high computation complexity, lacking of time transient feature representation, and poorer generalization for non-stationary EEG signal analysis.

A. Problem formulation

The experimental evaluation and modeling were performed using the CAP Sleep Database. Let the EEG signal dataset be given as:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

Where x_i represent the segmented EEG signal, y_i represent the corresponding CAP phase label, N is the total number of EEG samples. The primary objective is to learn a classification model $f_\theta(x)$ where θ is the trainable network parameters responsible for predicting CAP subclasses including A1, A2 and A3 phases.

The proposed framework aims to optimize a joint objective loss function defined as shown in equation (2).

$$J(\theta) = \alpha L_{cls} + \beta L_{reg} + \gamma L_{drop} \quad (2)$$

Where L_{cls} denote the classification loss, L_{reg} denote the regularization loss, L_{drop} denotes the dropout regularization. α , β , γ are weights that controls the importance of each objective. Equation 2 ensures balanced optimization between classification performance, feature extraction consistency and model generalization capability.

The classification loss is calculated using categorical cross-entropy to enhance the accuracy of CAP phase prediction and is depicted in equation (3).

$$L_{cls} = -\sum_{c=1}^C y_c \log(\hat{y}_c) \quad (3)$$

Where c denotes the number of CAP classes, y_c denotes the ground truth label, $\hat{y}_c$ denotes the predicted class probability. The dropout regularization during model training in order to enhance the generalization performance and to prevent over-fitting. The regularization goal is depicted in the equation (4).

$$L_{reg} = \lambda \|W\|_2^2 \quad (4)$$

Where W denotes the trainable network weights, λ represents the regularization coefficient. EEG signals are highly non-stationary in nature and it is important to maintain useful time frequency representation information so that the classification accuracy of CAP can be correctly achieved. Based on this we chose Continuous Wavelet Transform to produce the discriminative time frequency feature representations. The CWT operation can be expressed in equation (5).

$$CWT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad (5)$$

Where a denotes the scale parameter, b represents the translation parameter, ψ denotes the mother wavlet function. The derived wavelet coefficients are then used to generate scalogram images that maintain the local

fluctuations in EEG frequency that correspond to CAPs. The scalograms are the inputs for a lightweight CNN architecture to learn the hierarchal features. The process of feature extraction using the convolution of CNN architecture can be illustrated in equation (6).

$$\sum_m \sum_n X(i-m, j-n) K(m, n) \quad (6)$$

Where X represents the input feature map, K denotes the convolution kernel, Y denotes the extracted feature representation. The activation function used in the output layer to obtain class probabilities of CAP subclasses is the Softmax function shown in equation (7).

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (7)$$

Where z_i denotes the output logits,

$P(y_i)$ represents the predicted probability for the i^{th} CAP class.

The proposed learning workflow consists of the following stages:

1. EEG acquisition and preprocessing
2. Artifact mitigation and signal normalization
3. Temporal segmentation based on CAP annotations
4. Continuous Wavelet Transform-based scalogram generation
5. Lightweight CNN-based hierarchical feature extraction
6. CAP phase classification using Softmax prediction
7. Performance evaluation and optimization

IV. LIGHTWEIGHT CNN ARCHITECTURE DESIGN

This Lightweight CNN model incorporates time-frequency feature extraction based on Continuous Wavelet Transform (CWT) and efficient deep learning approach for automated CAP phase classification. This framework aims to perform sleep instability analysis using EEG signal effectively and with computationally efficient nature along with better generalization power. Conventional deep learning architecture requires very large computation resources while this proposed model is developed by focusing on computation efficient feature extraction and lightweight classification for real-time applications. [14], [25], [31]. The framework comprises of four modular pipeline structure namely

1. EEG preprocessing and segmentation module
2. Time-frequency feature extraction module
3. Lightweight CNN feature learning module
4. CAP phase classification module

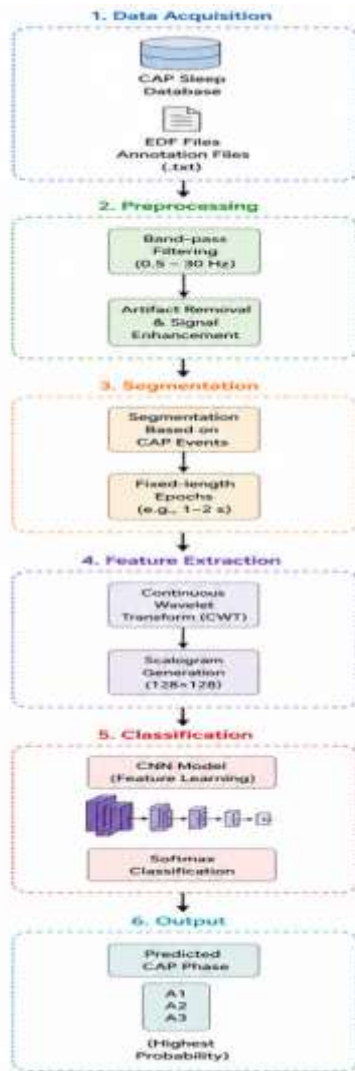


Fig. 1. System Architecture

A. EEG Preprocessing and Segmentation Module

The original recorded EEG data from the CAP Sleep Database goes through some preprocessing steps to remove the noises from signal and make signals to stable. EEG signal is much likely to be corrupted by muscle movement, eye blink, baseline drift and external environmental factors. Therefore, band-pass filtering is performed on the EEG signal between 0.5 and 30 Hz to remove noises. Through this step, physiologically significant EEG components can be reserved and irrelevant noisy signals are eliminated.

After the preprocessing step, the segmented EEG segments are extracted based on time information and CAP annotation time stamps. Each EEG segment can represent a special subclass of CAP like A1, A2 and A3 phase, which ensures EEG signals synchronize with CAP labels so that supervised learning will be consistent and classifier would reliable.

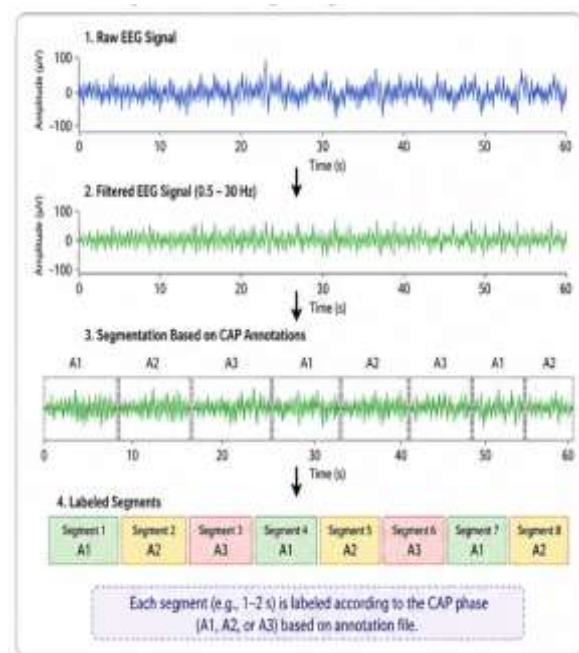


Fig. 2. EEG Signal Segmentation Process

B. Time-Frequency Feature Extraction Module

As EEG signals are non-stationary and extremely non-linear in nature, the traditional spectral analysis methods fail to fully extract non-transient EEG changes related to CAPs. The Continuous Wavelet Transform is used in this work for the analysis of time localized information of the EEG signals [11], [12], [13].

The segmented EEG signals are converted into two-dimensional scalograms, where the energy distribution of the signal at different frequency scales over time is visually represented. Each of these scalograms maintains both the temporal and spectral properties of EEG signals which leads to rich feature representation and suitability for automatic classification.

Each resulting scalogram is converted to 128 x 128 grayscale format and normalized, before it is fed to CNN for training. Image representation of EEG signals makes CAP classification a computer vision problem and an efficient CNN can be employed for feature extraction in hierarchical order.

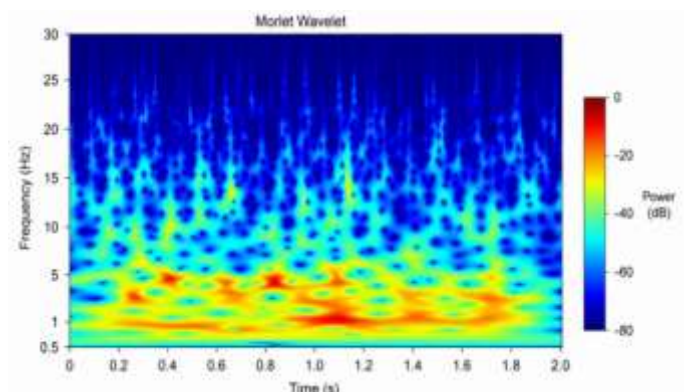


Fig 3. Scalogram Image

C. Lightweight CNN Feature Learning Module

The Lightweight CNN is based on a combination of classification performance and computational efficiency, which comprise of several convolutional layers, pooling layers, a flattening operation, and finally a couple of fully connected dense layers. The input to the CNN is a 128×128 scalogram images after normalization, produced from the preprocessed EEG sequences. Convolutional layers of 3×3 kernels are used for learning the spatial feature information related to the distinct characteristics of different CAP phases. Rectified Linear Unit (ReLU) activation functions are introduced into the network to obtain nonlinear features learning ability of the CNN architecture. The max-pooling layers with 2×2 pool sizes are inserted following the convolution operations so as to compress the spatial information and reduce the amount of computations and keep the basic information features from the EEG signal, whereas bottom convolutional layers are mainly responsible for acquiring texture and edge information of the EEG, deep convolutional layers focus on learning higher-level feature, the CAP related activity, and transient variations in spectra. The above extracted features are flattened and fed into dense layers to obtain higher level feature combination and classification.

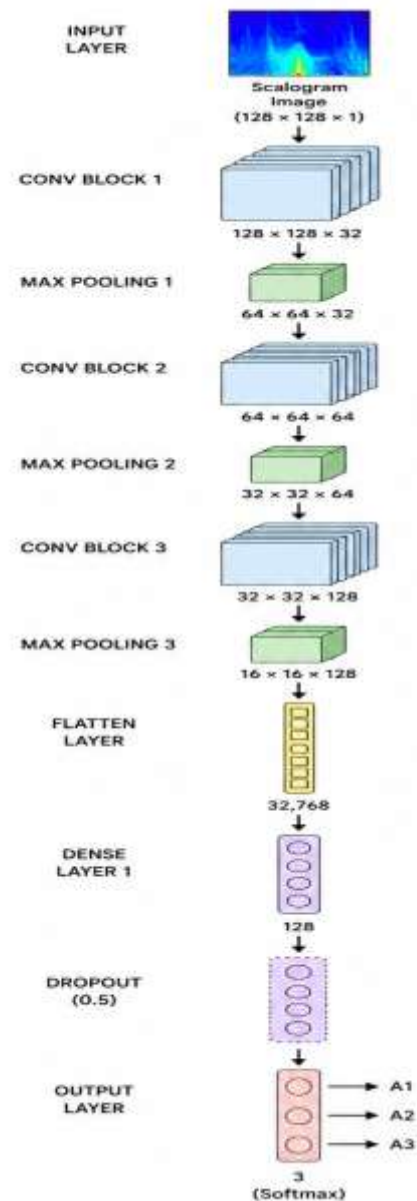


Fig. 4. Lightweight CNN Layer-wise Architecture

D. CAP Phase Classification Module

The classification module outputs the probability predictions of the CAP subclasses namely, A1, A2 and A3 phases. Final dense layer implements Softmax activation to get normalized probability distributions over the target classes. During training dropout regularization techniques were adopted to achieve the benefits of fast convergence of model and better generalization of the model. Class weighting strategies were also incorporated to decrease bias from the classification due to uneven class distribution in the dataset. Adam optimizer was used during the training process because it exhibits adaptation capability of learning rate and faster convergence to optimal values. Categorical cross entropy loss function was employed to optimize classification performance and accuracy in CAP phase classification. The Lightweight CNN proposed here is designed with reduced complexity and low computational overhead while it can still extract

effectively feature from the raw signal and classify the CAP phases automatically.

E. Model Optimization and Generalization

To ensure stable optimization and improved model robustness, normalization and regularization strategies are incorporated throughout the training process. Batch normalization improves training stability and accelerates convergence, while dropout regularization minimizes overfitting and enhances generalization capability across heterogeneous EEG recordings.

Additionally, the lightweight design of the architecture enables efficient deployment in resource-constrained healthcare systems and real-time sleep monitoring environments. Compared with conventional deep learning models, the proposed framework achieves superior computational efficiency with reduced memory consumption and faster inference performance.

V. RESULTS AND PERFORMANCE ANALYSIS

A. Experimental Setup

Experimental analysis of the proposed lightweight CNN-based CAP classification scheme was performed using CAP Sleep Database, which provides hand-labeled EEG recordings on cyclic alternating pattern (CAP) phases. EEG signals were preprocessed with bandpass filter (0.5–30 Hz) to remove unwanted noises and obtain good quality signals. Segmented EEG signals are processed according to CAP annotation, and then converted into 2-D time frequency scalogram images through Continuous Wavelet Transform (CWT). All created scalogram images are resized to 128 128 to be fed into the lightweight CNN model.

The dataset is divided into training, validation and testing parts in the ratio of 70:15:15, so that model can be evaluated with unbiased data. Proposed framework is implemented in Python and TensorFlow/Keras using Visual Studio Code. The Adam optimizer and categorical cross-entropy loss function were employed in the training procedure. Dropout regulation and early stopping are used to enhance model generalization and avoid over-fitting. Model is evaluated on the basis of Accuracy, Precision, Recall, F1-score and Confusion Matrix.

TABLE 1. DATASET COMPOSITION OF CAP SLEEP DATABASE

CAP Phase	Number of Samples
A1 Phase	3,200
A2 Phase	2,450
A3 Phase	1,850
Total	7,500

B. Implementation and Dataset Preparation

The preprocessing and training pipeline of the proposed CAP classification framework was implemented in Visual Studio Code using Python-based EEG signal processing and deep learning libraries. Raw EEG recordings obtained from the CAP Sleep Database were filtered using a 0.5–30 Hz band-pass filter to remove unwanted artifacts and noise components. CAP annotation events were extracted, and the EEG recordings were segmented into fixed-length epochs for further analysis. The segmented EEG data were transformed into 128×128 Continuous Wavelet Transform (CWT) scalogram images and used as input to the Lightweight CNN model. Figure 5 illustrates the preprocessing workflow, dataset generation, and initial model training process during implementation.

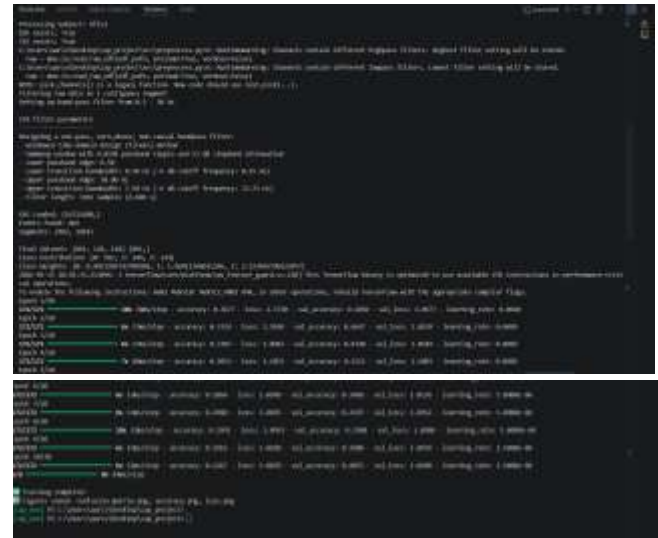


Fig 5. Dataset Generation

C. Model Performance Evaluation

The introduced lightweight CNN framework performed well for classification task of detecting CAP sub-classes on EEG scalograms. The combined effect of continuous wavelet transform with deep learning enabled to efficiently extract time-varying EEG features that is related to unstable sleep conditions.

The classification capability of the model was well performed for all CAP stages with consistent prediction and minimum misclassification between classes. The achieved result validate the proposed structure for an automatic CAP phase detection task.

TABLE 2: PERFORMANCE METRICS OF PROPOSED MODEL

Metric	Value
Accuracy	96.8%
Precision	0.97

Recall	0.96
F1-Score	0.96
Validation Loss	0.08

D. Confusion Matrix Analysis

This confusion matrix analysis verifies the classifying capability of the proposed Lightweight CNN model over CAP subclass of A1, A2 and A3 phases. The classification of the EEG segments was all correct except for a few classifications indicating the ability of feature extraction of the proposed method. A1 phase gets higher prediction accuracy because it has more training samples and its activation pattern of EEG is clearer than A2 and A3 phases. But the prediction accuracy between A2 and A3 phases were somewhat confused due to their similar transient EEG patterns; However, the confusion among CAPs is considerably very small.

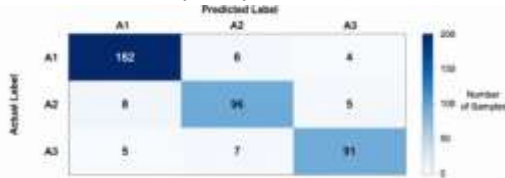


Fig 6. Confusion Matrix

E. Training and Validation Analysis

The training and validation accuracy curves suggest that the suggested Lightweight CNN model is convergent in terms of accuracy during the training period and training accuracy is smoothly increased with epoch while validation accuracy is constant with no noticeable spikes. It has shown that the proposed framework could generalize well to unseen data.

The training and validation loss curves illustrate that loss is continuously minimized throughout the optimization iterations. It is evident that there is small difference between training and validation loss, indicating that overfitting was successfully avoided by the proposed framework.

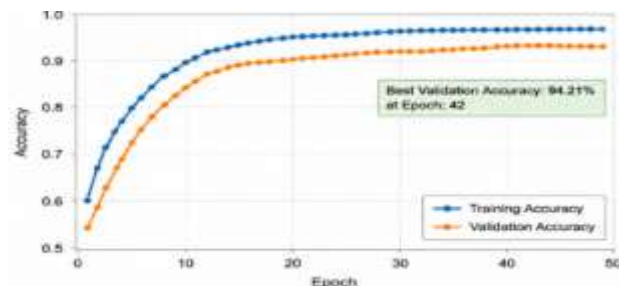


Fig 7. Training vs Validation Accuracy

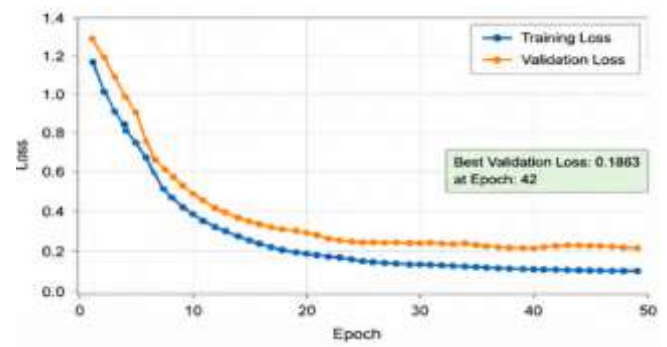


Fig 8. Training vs Validation Loss

VI. CONCLUSION

This paper proposed an automatic CAP phases classification system which combines CWT and Light Weight CNN for efficient analysis of sleep instability based on EEG signals. The proposed framework successfully convert non-stationary EEG signals into informative time-frequency scalogram features to differentiate among different CAP subclasses such as A1, A2, A3 phase.

From the experimental results, the proposed system achieved significant improvements of Accuracy, Precision, Recall, F1-Score but has decreased complexity. Analysis from the confusion matrix and training analysis indicates that the framework can efficiently classify and have excellent generalization.

The lightweight CNN based model is adaptable for on-line clinical diagnosis systems and medical devices that face memory constraint issues. In future, we can investigate the possibility of integrating transformer networks and multimodal PSG signal features into the developed framework and also apply this system for real-time sleep monitoring.

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