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# ResFormer-CAP-Net: A Hybrid Deep Learning Model for Automated CAP A-Phase and Subtype Classification

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***Abstract*** **–** Cyclic Alternating Pattern (CAP) is a crucial biomarker for assessing sleep quality and stability, as well as diagnosing sleep disorders. In clinical practice, manually detecting CAP A-phases and their subtypes by analyzing full-night electroencephalography (EEG) recordings is a time-consuming, labor-intensive, and error-prone process. In this study, a novel hybrid deep learning model, ResFormer-CAP-Net, is proposed for the automated classification of CAP A-phase and its subtypes. This model integrates ResNet-18 for feature extraction and Transformer layers for temporal modeling. The proposed model was evaluated using EEG recordings from healthy and sleep-disordered individuals in the publicly available CAP Sleep Database (CAPSD). Evaluations on balanced datasets demonstrated that ResFormer-CAP-Net achieved state-of-the-art performance, with 79.97% accuracy for A-phase classification and 81.88% accuracy for subtype classification. Additionally, the effectiveness of four different EEG channels was analyzed, revealing that the F4-C4 channel provided the highest accuracy for A-phase classification, while the C4-P4 channel performed best for subtype classification. The number of Transformer layers was also optimized, with experiments showing that using two Transformer layers resulted in the highest classification performance.

*Keywords – Cyclic Alternating Pattern, Deep Learning, Sleep, Electroencephalogram, Vision Transformers.*

## I. INTRODUCTION

Sleep is one of the most fundamental aspects of human life and is defined as a complex physiological process essential for the repair, restoration, and proper functioning of the body and mind. It plays a critical role in numerous biological functions, including immune regulation, hormonal balance, cognitive performance, metabolic homeostasis, and overall well-being [1], [2]. Inadequate or poor-quality sleep has been linked to numerous health issues, including cardiovascular diseases, neurodegenerative disorders, obesity, and mental health disorders [3], [4]. Additionally, sleep deficiency can lead to many problems like impaired cognitive function, reduced productivity, mood disorders and an increased risk of accidents [1], [5]. Given the profound impact of sleep on health and daily functioning, understanding and analyzing sleep structures are crucial for diagnosing sleep-related disorders and improving sleep quality.

Polysomnography (PSG), also known as a sleep study, is the gold standard method for sleep analysis, sleep quality assessment, and sleep disorder diagnosis [6]. This technique records a comprehensive set of physiological signals, including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), electrooculography (EOG), airflow, and respiratory parameters, during an overnight sleep examination in a laboratory setting. Among these, EEG plays a pivotal role in understanding brain activity during sleep, scoring sleep stages, and detecting microstructural patterns indicative of sleep stability and arousal mechanisms. One such EEG-based phenomenon that provides critical insight into sleep microstructure and stability is the Cyclic Alternating Pattern (CAP). CAP is defined as a periodic EEG activity observed exclusively during Non-Rapid Eye Movement (NREM) sleep and represents a fundamental marker of sleep instability and arousal regulation [7], [8]. This phenomenon encompasses transient, phasic events in sleep microstructure, such as K-complexes, vertex sharp transients, delta bursts, and polyphasic bursts. CAP consists of cyclic A-phases, reflecting brief surges in cortical activity lasting between 2 to 60 seconds, followed by B-phases, which correspond to periods of background sleep rhythm with a similar duration. The A-phase is further classified into three subtypes (A1, A2, and A3) based on EEG amplitude, frequency characteristics, and associated physiological responses. Fig. 1 illustrates these subtypes in an example EEG signal segment from CAP Sleep Database (CAPSD) [7], [9]. The clinical relevance of CAP and its subtypes is well established in sleep medicine, as their distribution, duration, and occurrence patterns have been strongly correlated with various neurological and sleep disorders, including insomnia [10], periodic limb movement disorder (PLMD) [11], nocturnal frontal lobe epilepsy (NFLE) [12] and REM behavior disorder (RBD) [13].

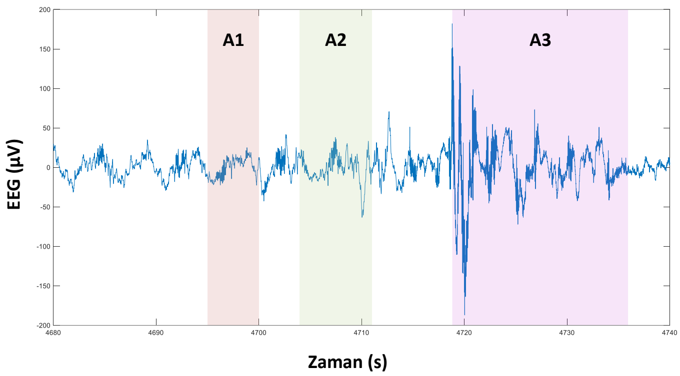


Fig. 1 Illustration of CAP A-phase subtypes (A1, A2, A3) in an example EEG segment from the CAPSD [7], [9].

CAP events and their subtypes are scored by sleep specialists through manual analysis of EEG recordings, which typically span 6 to 9 hours of overnight monitoring in a clinical setting [14]. Given the extensive duration of these recordings, conducting a second-by-second analysis is highly time-consuming and labor-intensive [15]. Moreover, the accuracy of CAP scoring is susceptible to inter-scorer variability, as it heavily depends on the expertise and experience of the specialist [16]. These challenges associated with CAP scoring highlight the urgent need for reliable and accurate automated CAP detection methods that can enhance efficiency, reduce subjectivity, and improve reproducibility in clinical settings.

Various studies have investigated automated CAP A-phase and subtype detection using both traditional machine learning (ML) and deep learning (DL) approaches. Traditional ML methods typically involve extracting handcrafted features from EEG signals and classifying them using algorithms such as support vector machines (SVM) [17], k-nearest neighbors (k-NN) [18], ensemble bagged trees (EBaT) [18], and multi-layer perceptrons (MLP) [19]. While these approaches have achieved promising results, their dependence on handcrafted feature extraction and dataset-specific parameter tuning has restricted their applicability to broader datasets. To address these challenges, recently, DL-based methods, such as Convolutional Neural Networks (CNNs) [15], [20], [21] have been developed to enable automated CAP classification with improved and automated feature learning capabilities. Recent studies have also explored hybrid models that integrate CNNs with attention mechanisms to further enhance classification accuracy. Despite these advancements, challenges such as high computational complexity, data imbalance, and the need for even higher classification accuracy remain significant research concerns in the field.

To address these limitations, this study proposes ResFormer-CAP-Net, a novel hybrid DL model designed for the classification of both CAP A-phase (A-phase vs non-A-phase) and its subtypes (A1 vs A2 vs A3). ResFormer-CAP-Net integrates the spatial feature extraction capabilities of CNNs with the temporal modeling strengths of Transformer networks [22], providing a more comprehensive approach to EEG-based CAP detection. Additionally, this study evaluates the model's performance across four EEG channels, namely C4-P4, F4-C4, Fp2-F4, and P4-O2, for both CAP scoring tasks. Finally, the optimal model configuration is determined by fine-tuning the number of Transformer layers in ResFormer-CAP-Net to achieve the best balance between accuracy and computational efficiency.

## II. MATERIALS AND METHOD

### A. *Dataset*

The publicly available CAPSD [7], [9] was used in this study to develop and evaluate the proposed ResFormer-CAP-Net model. CAPSD serves as a benchmark dataset for detecting CAP A-phase and its subtypes, making it a suitable choice for this research. The dataset contains full-night PSG recordings of 108 subjects, including 92 patients with sleep disorders and 16 healthy individuals. Each PSG recording includes at least three EEG channels, EMG and EKG. The CAP A-phase and its subtypes were annotated by expert neurologists following the Terzano's reference atlas of rules. In this study, only EEG signals were utilized for classification of A-phase and its subtypes. To evaluate the ResFormer-CAP-Net on both healthy and sleep-disordered subjects, a subset of 12 subjects was selected. Specifically, healthy individuals were first examined, and only those with an EEG sampling frequency of 512 Hz were included, resulting in a selection of 6 subjects. To maintain balance, an equal number of NFLE patients (n=6) were also selected. Table 1 presents the selected subjects.

### B. *Preprocessing*

A series of preprocessing steps were applied these selected PSG recordings before feeding them to the ResFormer-CAP-Net. First, four EEG channels (C4-P4, F4-C4, Fp2-F4, and P4-O2) were extracted from the selected PSG recordings to investigate the effect of EEG channels on model performance and to determine the most informative EEG channel. Since CAP occur exclusively during the NREM sleep stage [7], only the NREM stage was retained while signals corresponding to other sleep stages were discarded. This was achieved using sleep stage labels annotated according to the Rechtschaffen & Kales (R&K) rules [23]. Following this, each EEG recording was segmented into 11-second epochs with a 3-second shift interval. To mitigate the class imbalance issue caused by the higher prevalence and longer duration of B-phase (non-A-phase) compared to A-phase, only one out of every ten non-A-phase epochs was retained. Next, to simultaneously analyze both the temporal and spectral characteristics of the signals, each EEG epoch was transformed into a time-frequency representation using Continuous Wavelet Transform (CWT) [21]. The resulting scalograms were saved as 64 x 64 x 3 images, with label corresponding to sixth second of the epoch. Fig. 2 illustrates example scalogram images obtained for A-phase, B-phase, and their subtypes.

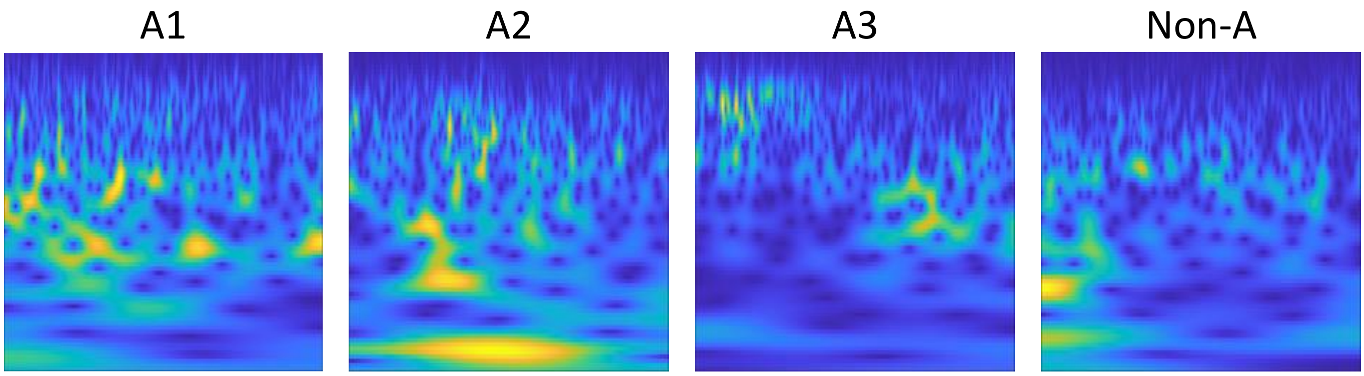


Fig. 2 Example scalograms of EEG epochs for CAP A-Phase (A1, A2, A3) and B-Phase (Non-A phase).

Table 1 presents the number of epochs obtained from each subject for A-phase and its subtypes. As seen in the table, there is an imbalance between classes, which may cause the model to produce biased results toward the majority class. To address this dataset imbalance issue, the number of samples in all classes was equalized by down-sampling. After balancing, each CAP A-phase subtype contained 3,509 epochs, while the A-phase and non-A-phase classes each included 10,527 epochs.

Table 1. The number of A-phase subtypes (A1, A2, and A3), total A-phase), and non-A phase epochs.

| **Subjects** | **Number of epochs** | | | | |
|---|---|---|---|---|---|
| | **A1** | **A2** | **A3** | **Total A** | **Non-A** |
| N1 | 744 | 247 | 567 | 1558 | 978 |
| N2 | 397 | 233 | 1361 | 1991 | 792 |
| N3 | 219 | 217 | 790 | 1226 | 877 |
| N5 | 973 | 108 | 350 | 1431 | 863 |
| N10 | 490 | 155 | 1190 | 1835 | 670 |
| N11 | 577 | 193 | 269 | 1039 | 947 |
| NFLE1 | 1120 | 191 | 322 | 1633 | 789 |
| NFLE2 | 465 | 270 | 2028 | 2763 | 700 |
| NFLE3 | 425 | 197 | 1681 | 2303 | 872 |
| NFLE4 | 669 | 986 | 785 | 2440 | 872 |
| NFLE5 | 725 | 401 | 1053 | 2179 | 835 |
| NFLE7 | 1277 | 311 | 1089 | 2677 | 843 |
| **Total** | 8081 | 3509 | 11485 | 23075 | 10038 |

*Proposed ResFormer-CAP-Net*

In this study, a novel model, called ResFormer-CAP-Net, is proposed for the accurate and automated classification of CAP A-phase and its subtypes. ResFormer-CAP-Net integrates CNN architecture and Transformer layers [22], leveraging the spatial feature extraction power of CNNs and the long-range temporal modeling capability of Transformers to effectively capture both spatial and temporal dependencies in EEG signals. Fig. 3 illustrates the overall architecture of ResFormer-CAP-Net. The proposed network consists of three main stages: a feature extraction module based on CNN (specifically ResNet-18 [24]), a Transformer encoder for temporal modeling, and a classification layer for predicting CAP A-phase (A-phase vs non-A-phase) or its subtypes (A1 vs A2 vs A3).

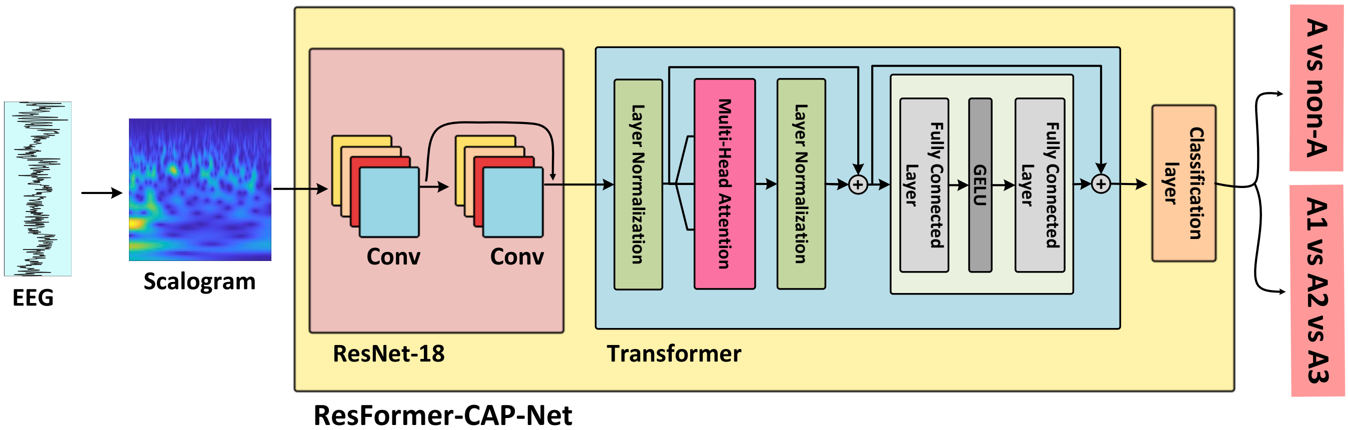


Fig. 3. The architecture of the proposed ResFormer-CAP-Net.

ResNet-18 receives 64 × 64 scalogram images obtained from EEG epochs as input. Therefore, the first layer of ResNet-18 is modified to accept 64 × 64 × 3 input images. During the feature extraction stage, these images are processed through the CNN model, where hierarchical features are extracted. ResNet-18 [24] was chosen as the backbone due to its efficiency in capturing spatial hierarchies in image-based data while optimizing gradient flow through residual connections. The extracted features are obtained from ResNet-18's final pooling layer (pool5). Given the input scalogram image $X$, the extracted feature maps $F$ are defined as follows.

$$F = ResNet18(X) \tag{1}$$

To better model long-term dependencies and temporal relationships, these extracted features are passed through n Transformer encoder [22] layer in the second stage The value of n varies between 1 and 3, determined based on experimental results. As shown in Fig. 3, each Transformer layer consists of a multi-head self-attention (MHSA) mechanism, followed by two fully connected layers. Feature maps are first passed through layer normalization. Then, the multi-head self-attention (MHSA) mechanism is applied to identify the most important feature representations. This mechanism evaluates the relationships between each input feature and all others, allowing the model to learn long-term dependencies. A self-attention mechanism operates using query ($Q$), key ($K$) and value ($V$) matrices and is defined as follows.

$$SelfAttention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

Where $d_k$ is a scaling factor for normalization. The multi-head self-attention mechanism performs this operation in parallel across multiple attention heads. The output of MHSA is expressed as follows:

$$Z_{MHSA} = MHSA(Z_{in}) \tag{3}$$

The output of MHSA is passed through layer normalization and added to the input features. Then, it is processed through two consecutive fully connected layers to obtain the final feature representations for a Transformer layer. The final feature representation obtained from the last Transformer layer is passed to the classification layer to classify either A-phase vs. non-A-phase or A1 vs. A2 vs. A3.

## III. RESULTS

This section presents the experimental results obtained from the proposed ResFormer-CAP-Net. All experiments including preprocessing were conducted on a high-performance workstation equipped with an NVIDIA GeForce RTX 4090 GPU, 128 GB RAM, and a 13th generation Intel Core i9-13900K CPU. All coding and implementation were performed on in MATLAB R2024a. The balanced datasets prepared for both tasks during the preprocessing stage were divided into 80% training and 20% validation. The ResFormer-CAP-Net was trained using the Adam optimizer, with a batch size of 64, a learning rate of 0.001, and a maximum of 20 epochs. To mitigate overfitting, an early stopping mechanism was applied, automatically stopping training if validation loss did not improve over four consecutive epochs. To evaluate the classification performance of the proposed model, commonly used performance metrics, including accuracy, sensitivity, specificity, precision, and F1-score were employed [20]. These metrics were computed from confusion matrix.

Table 2 presents the accuracy results obtained by ResFormer-CAP-Net for each EEG channel as the number of Transformer layers increases. For CAP A-phase classification, the highest accuracy of 79.97% was achieved using the F4-C4 channel with two Transformer layers. Similarly, the Fp2-F4 channel exhibited a comparable performance, reaching 79.82% accuracy with the same number of Transformer layers. In contrast, the P4-O2 channel demonstrated the lowest accuracy, remaining around 75% across all Transformer configurations. For CAP subtype classification, the highest accuracy of 81.88% was obtained using the C4-P4 channel with two Transformer layers. Likewise, the Fp2-F4 channel yielded a similar accuracy of 81.61%, while the P4-O2 channel consistently produced the lowest accuracy values, remaining around 78%. Table 3 summarizes the detailed performance metrics for the best-performing configuration in each CAP classification task. Since the dataset was balanced, the values of these performance metrics closely align with the accuracy values. These results indicate that ResFormer-CAP-Net achieves high classification performance across different EEG channels and Transformer configurations, with optimal results observed for two Transformer layers in both tasks.

Table 2. Accuracy (%) of the ResFormer-CAP-Net for Different EEG Channels and Transformer Layers.

| **Classification task** | **#Transformer** | **C4-P4** | **F4-C4** | **Fp2-F4** | **P4-O2** |
|---|---|---|---|---|---|
| A-phase | 1 | 77.49 | 79.04 | 79.13 | 75.64 |
| | 2 | 78.26 | 79.97 | 79.82 | 75.87 |
| | 3 | 77.13 | 79.31 | 78.67 | 75.73 |
| Subtype | 1 | 81.18 | 80.72 | 81.42 | 78.39 |
| | 2 | 81.88 | 81.05 | 81.61 | 78.88 |
| | 3 | 81.21 | 80.64 | 81.12 | 78.13 |

Table 3. Performance metrics (%) of ResFormer-CAP-Net for the best-performing configurations.

| **Classification task** | **Acc** | **Sen** | **Spe** | **Pre** | **F1** |
|---|---|---|---|---|---|
| A-phase | 79.97 | 79.35 | 80.26 | 80.18 | 79.73 |
| Subtype | 81.88 | 81.88 | 84.67 | 82.12 | 81.92 |

## IV. DISCUSSION

The experimental results obtained the proposed model demonstrated the ResFormer-CAP-Net in the automated classification of CAP A-phase and its subtypes. The results indicate that the integration of ResNet-18 model for feature extraction and Transformer layer for temporal long dependencies relationships provides a significant performance enhancement in CAP classification tasks. The F4-C4 and Fp2-F4 channels achieved the highest accuracy rates for CAP A-phase detection, suggesting that frontal and central electrode placements are particularly informative for distinguishing CAP-related activity. In contrast, the P4-O2 channel consistently exhibited lower classification accuracy across all Transformer configurations, implying that occipital electrodes may contribute less discriminative information for CAP detection. The effect of Transformer depth was also examined in the study. The results show that using two Transformer layers provided the highest classification accuracy for both CAP A-phase and subtype classification tasks. While increasing the number of Transformer layers beyond two did not significantly improve performance, a slight decline was observed in some cases. This suggests that excessive Transformer depth may lead to overfitting or redundancy in feature extraction, particularly when working with limited EEG data.

Table 4 compares ResFormer-CAP-Net with previous state-of-the-art studies in terms of methodology, the number of subjects used in the dataset, reported performance metrics, and key limitations. As observed from the table, the majority of existing studies rely on traditional ML methods [18], [19], [25], which require handcrafted feature extraction processes. While these methods have shown moderate success, they are often limited by dataset-specific parameter tuning and feature selection biases. From a different perspective, most studies have focused exclusively on CAP A-phase classification, with limited efforts directed toward subtype classification. Among these, Halder et al. [20] achieved the highest reported accuracy rates of 90.31% for A-phase classification and 86.72% for subtype classification using a 1D-CNN with an attention mechanism. However, despite the high accuracy, the authors reported significantly lower F1-scores of 65.73% for A-phase and 59.59% for subtypes, suggesting that their model struggled with imbalanced class distributions. This highlights the importance of considering F1-score over accuracy when working with highly imbalanced datasets. In contrast, in this study, a balanced dataset was used, leading to 79.97% accuracy for A-phase classification and 81.88% accuracy for subtype classification. Unlike Halder et al.'s study [20], ResFormer-CAP-Net also achieved F1-scores of 79.73% for A-phase and 81.92% for subtypes, demonstrating more stable performance across different classes. This result underscores the significance of dataset balancing techniques in achieving more reliable and unbiased classification results. Furthermore, ResFormer-CAP-Net eliminates the need for complex and labor-intensive handcrafted feature extraction processes, which are required in traditional ML-based approaches. This hybrid architecture improves classification performance while reducing the dependence on manual preprocessing and expert-driven feature engineering.

Table 4. Comparison of the proposed ResFormer-CAP-Net with previous studies.

| **Ref, year** | **Class** | **Method** | **Results (%)** | **Limitations** |
|---|---|---|---|---|
| [19], 2024 | A–A' | hand-crafted feature extraction feature selection, MLP | **Acc:** 73.0, **Sen:** 77.0 | Low accuracy, hand-crafted feature extraction, only A-phase detection |
| [26], 2024 | A–A' | 11-s epochs, Wigner-Ville distribution, and ResNet18 | **Acc:** 77.5, **Sen:** 75.9 (balanced data) | Low accuracy, only A-phase detection, testing only on healthy individuals |
| [25], 2024 | A–A' | 2-s epochs, sub-band decomposition, hand-crafted feature extraction, kNN | **Acc:** 79.1**, F1:** 79.2 (balanced data) | Hand-crafted feature extraction, only A-phase detection, testing only on healthy individuals |
| [18], 2023 | A–A'<br>A1-A2-A3 | 2-s epochs, subband decomposition, hand-crafted feature extraction, EBaT for A-phase, kNN for subtype | **Acc:** 83.6 **F1:**74-88<br>**Acc:** 78.8, **F1:** 80-63-85 | Hand-crafted feature extraction, low accuracy for subtype class |
| [15], 2023 | A–A' | 2-s epochs, three 1D-CNN, ensemble averaging | **Acc:** 82-87, **Sen:** 72-80 | Complex, and post-processing |
| [20], 2023 | A–A'<br>A'-A1-2-3 | 30-s epochs, 1D-CNN with attention | **Acc:** 90.31, **F1:** 65.73<br>**Acc:** 86.72, **F1:** 59.59 | Low F1, testing only on healthy individuals |
| [21], 2023 | A-A'<br>A1-A2-A3 | 31-s epochs, MobileNetV2, transfer learning, fine-tuning for subtype | **Acc:** 80, **Sen:** 75<br>**Acc:** 80-75-71 **Sen:** 84-72-59 | Complex |
| **This study** | A–A'<br>A1-A2-A3 | 11-s epochs, ResFormer-CAP-Net | **Acc:** 79.97**, F1:**79.73<br>**Acc:** 81.88**, F1:**81.92 | Complex |

## V. CONCLUSION

In this study, we developed a novel hybrid DL model ResFormer-CAP-Net, for the automated classification of CAP A-phase and its subtypes. ResFormer-CAP-Net combines the well-known CNN architecture ResNet-18 for feature extraction with Transformers to capture temporal dependencies in EGG signals. Experimental results Experimental results show that F4-C4 and Fp2-F4 channels achieved the highest accuracy for CAP A-phase detection, while C4-P4 and Fp2-F4 channels performed best for subtype classification, emphasizing the importance of frontal and central EEG regions. The optimal number of Transformer layers was found to be two, as deeper configurations led to performance degradation due to overfitting. The use of a balanced dataset resulted in more reliable classification, yielding higher F1-scores compared to studies using imbalanced datasets.

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