EEG Based Deep Learning Model for Automated Classification of Frequent and Infrequent Readers

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***Abstract*—Reading comprehension is a complex cognitive process that involves semantic decoding, and schema integration influenced by reading practice. This study investigates the neural correlates of reading comprehension and explores how brain activation patterns differ between frequent and infrequent readers. Using Electroencephalography (EEG), the brain activation patterns were recorded from participants while performing the reading comprehension tasks. The EEG signal is recorded with a sampling rate of 1024 Hz to capture the dynamic changes in brain activation during reading tasks, revealing how frequent and infrequent readers differ in their cognitive processing and neural efficiency. The 21 channels of EEG signal acquired from 9 participants were pre-processed to obtain a 512 Hz band-limited signal. The pre-processed EEG signals were segmented before being fed into a twenty-four-layered convolutional neural network (CNN) model. The convolution stage extracts the temporal and spatial features, and the most significant features are extracted at the max-pooling stage. Frequent and infrequent readers are classified using the fully connected layer based on their EEG signals. The proposed model obtained a classification accuracy of 93.94%.**

***Keywords*—Reading comprehension, Frequent readers, Infrequent readers, Electroencephalogram, Deep learning algorithm**

I. Introduction

Reading is a crucial cognitive skill that involves attention, information organization, comprehension, working memory, and memory retrieval. It is essential for everyday activities and academic performance. Good reading skills require word recognition and phonological awareness, which can be achieved through frequent reading [5]. Reading comprehension involves understanding and integrating information with existing knowledge [3]. Frequent reading increases fluency, while infrequent reading decreases fluency.

Understanding the brain's functioning is crucial for reading comprehension processing [2]. This study focuses on the brain mechanisms and cognitive processes involved in reading. Despite the advances in psycholinguistic research on reading, it is still important to comprehend how different reader types differ in their ability to comprehend what they read [4]. Reading involves phonological awareness, word recognition, decoding information, and comprehension, which depends on the functioning of different areas in the brain. The letter and word formation requires the coordination of multiple language areas in the brain. Advances in technology in recent years have enhanced our ability to understand brain processing during reading [3].

Several neuroimaging techniques have revolutionized the study of brain functions such as Positron Emission Tomography (PET) [16], Magnetic Resonance Imaging (MRI) [13], and Functional MRI (fMRI) [14]. Despite these advances, Electroencephalography (EEG) remains a foundational technique for measuring the brain's electrical activity in real time. This method is cost-effective, portable, and radiation-free, with excellent temporal resolution, making it instrumental in identifying brain regions involved in cognitive tasks like reading [15]. EEG may also be employed to explore cognitive processes. EEG facilitates the analysis of electrical activity across both hemispheres, providing valuable insights into how the brain processes language.

This study investigates differences in brain functioning between frequent and infrequent readers using EEG signals, as frequent reading has enhanced reading comprehension skills. The hypothesis is that the EEG signals of frequent and infrequent readers will exhibit distinguishable patterns during reading comprehension tasks, such as synonyms, antonyms, analogies, and passage comprehension. A one-dimensional convolutional neural network (CNN) model is employed to automatically extract meaningful spatial and temporal features from the pre-processed EEG data, enabling the classification of participants into these two categories. By analyzing brain activation patterns, the CNN enables classification based on the assumption that neural activity related to reading proficiency differs between frequent and infrequent readers.

Traditional classifiers such as artificial neural networks, k-nearest neighbors, logistic regression, naïve Bayes, random forests, and support vector machines have been used to classify EEG signals for various applications. However, this approach is cumbersome and depends heavily on domain knowledge to select the right features and classifiers [17]. In contrast, deep learning offers an advantage by automatically learning discriminative features from raw EEG data, streamlining the process, and improving performance compared to the hand-crafted feature extraction process [18].

This study has limitations, including a small sample size of 9 participants, which may affect generalizability. However, using the windowing approach the size of the dataset is significantly increased. Additionally, the gender imbalance could influence the findings, and future research should aim for a more uniform distribution.

Despite these limitations, understanding differences in brain activation between frequent and infrequent readers has important real-life implications. For students with reading disorders such as Dyslexia and Attention Deficit Hyperactive Disorder (ADHD), identifying the brain patterns of frequent readers may lead to clinical interventions to improve reading skills. This research could also help develop personalized learning strategies in educational settings, making it a promising tool for clinical and academic applications.

The paper is structured as outlined below: Section II, Dataset Preparation, describes the subjects and procedure for the EEG recording and outlines the objectives of the study. Section III, Methodology, covers the preprocessing of EEG data, including the Z-Score threshold method, min-max normalization, and filtering, followed by the segmentation process. It also covers the Deep Learning Algorithm, discusses the use of CNN, and details the proposed CNN architecture. Section IV and V, present the results and findings from applying the CNN to the EEG data. Lastly, Section VI concludes the paper by briefing the observations.

II. Dataset Preparation

A. Subjects and procedure

Participants for this study were 10 right-handed ESL (English Speaker of Other Language) learners (3 male and 7 female), aged 21 to 30 (mean age 26), from the National Institute of Technology, Tiruchirappalli, India. All were postgraduate students with homogeneous English proficiency, confirmed by their admission through English-based entrance exams and interviews. Participants reported no severe health conditions or brain injuries, and none had any uncorrected vision. In the study, English was chosen as the stimulus language. Using English allows for exploring the cognitive dynamics involved in processing a language in an academic setting where English is the medium of instruction, providing valuable insights into neural adaptation in non-native speakers. The frequent and infrequent readers were initially classified based on their reading habits and later confirmed with the acquired results.

The details of each subject and their reading activity were obtained using a basic questionnaire to find the reading frequency of the subjects. The reading comprehension tasks included 15 synonyms, 16 antonyms, 22 analogies, and 17 passage comprehension questions, and clear instructions were provided at the beginning of each task. All four tasks were shown as visual stimuli on a screen during data acquisition. The participants were informed to avoid movements and to minimize eye blinking as much as possible during the recording. The ethical clearance and the participants' consent were obtained to conduct this study.

B. EEG Recording

The EEG signals were recorded using the Axxonet Brain Electrical Scan System (BESS) at EEG Laboratory, NIT Tiruchirappalli. A standard 10-20 electrode placement configuration was followed in this study. The EEG signals from the frontal region were collected by using the electrodes Fp1, F3, F7, Fz, Fp2, F4, and F8 electrodes. The Occipital region was covered by electrodes O1 and O2, the parietal region by P3, Pz, and P4, and the central region by electrodes C3, C4, and Cz. The signals from the temporal regions were obtained using the electrodes T3, T4, T5, and T6, that cover both the left and right temporal areas. Fz electrode was used as the reference electrode. The EEG signals were sampled at a frequency of 1024 Hz.

C. Objectives

This research aims to utilize the 1D CNN model to classify frequent and infrequent readers. The initial step involved the removal of outliers from the raw EEG data. The outliers were identified and removed from each channel of the EEG signal using the Z-score threshold method. The resulting EEG signals were scaled using the min-max normalization technique. The next step involved the filtration of normalized EEG signals using notch filters to remove the power-line interferences. The filtered EEG signals were then segmented into 20s window lengths. The segmented signals were then given to the CNN model for the training and testing phase. The proposed 1D CNN architecture performed automatic feature extraction from the time-series data by applying suitable convolutional filters thus enabling classification and brain activity analysis. The outline of the proposed framework is shown in Fig. 1.

III. Methodology

A. EEG data pre-processing

The activity of each brain region was captured by recording the electrical signals from the head surface. The electrical signals recorded from the head surface may not precisely depict the brain activity due to factors like signal attenuation, noise, and interference. Thus, the raw EEG data need to be processed before further analysis. The pre-processing involves

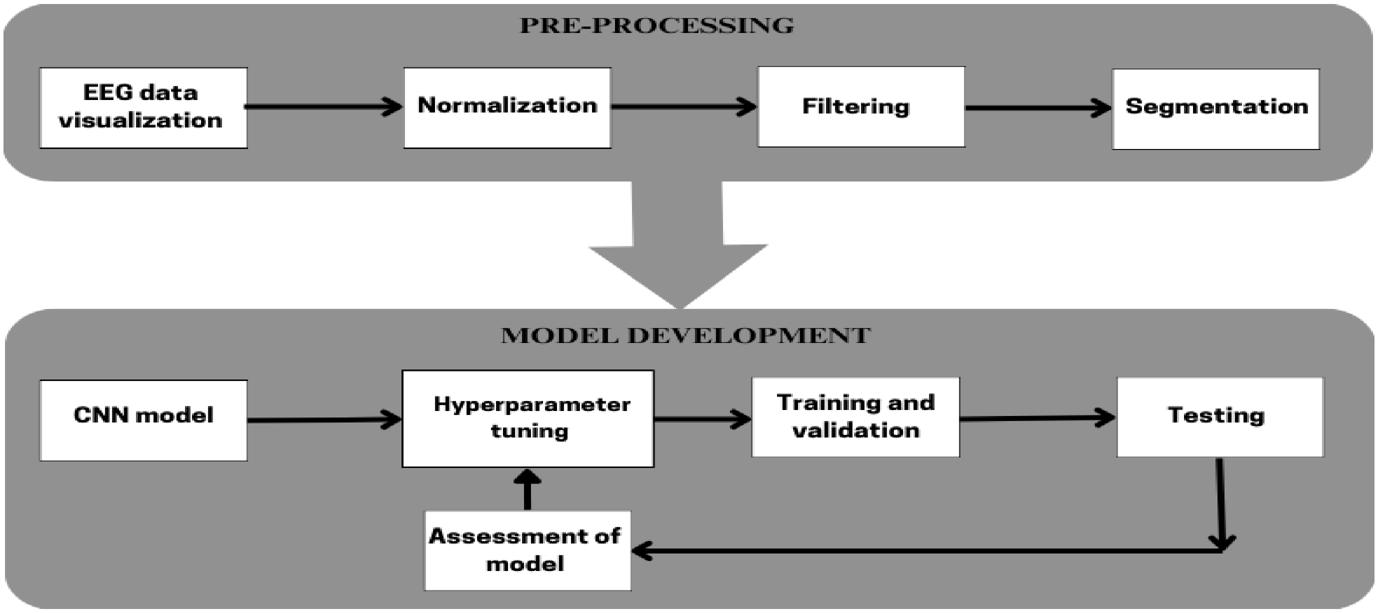

Fig. 1: Outline of the proposed framework

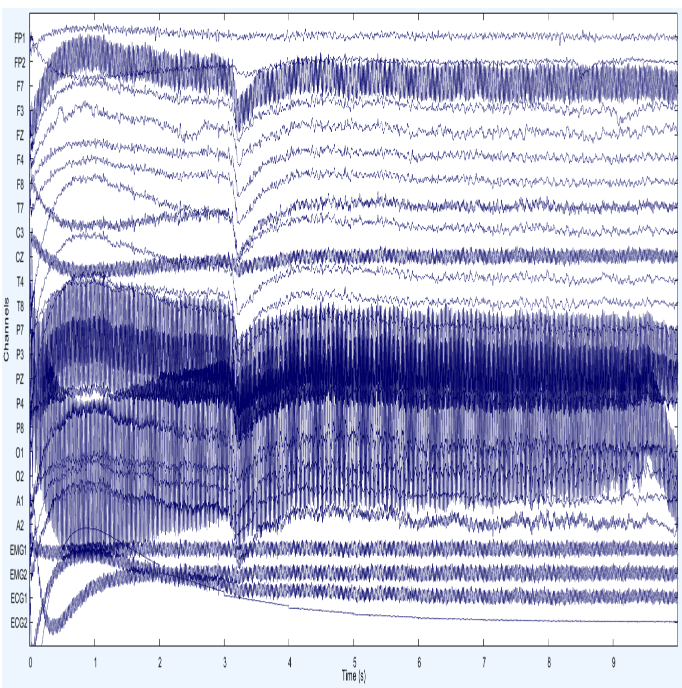

Fig. 2: Raw EEG signal

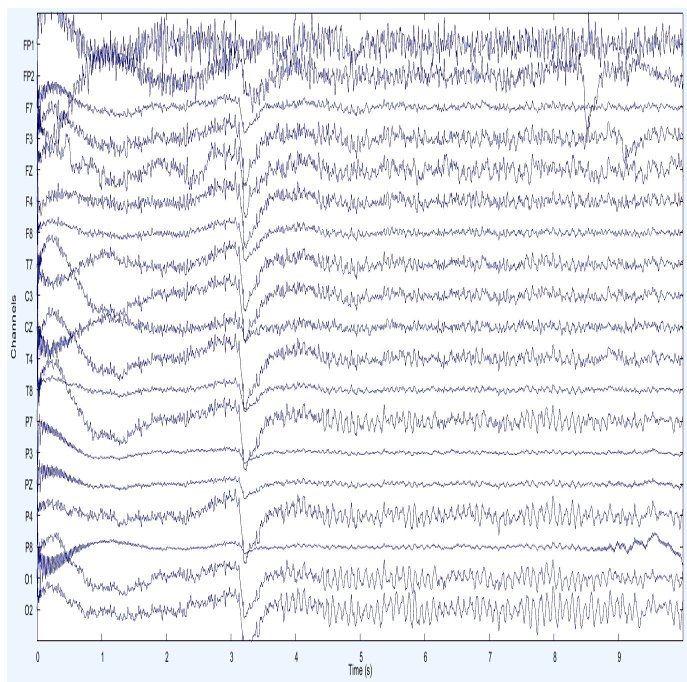

Fig. 3: Pre-processed EEG Signal

transforming the contaminated raw EEG data into noise-free data by removing the artifacts [10]. In this study, pre-processing steps included the removal of outliers, normalization, filtering, and segmentation. The raw and pre-processed EEG signals of a participant are shown in Fig. 2 and Fig. 3 respectively.

1) Z-Score threshold method: Outliers refer to data points that deviate significantly from the majority of the data, often indicating anomalies or errors. Removing outliers from the EEG data improves accuracy by reducing the effect of noise and artifacts, leading to more reliable and interpretable results. The Z-Score threshold method was employed to remove outliers. In this method, the mean and standard deviation of the signal values for each channel were computed. The outliers were identified as values that fell outside ±3 standard deviations from the mean. This method effectively reduced the noise while preserving the underlying neural signals during cognitive tasks, especially those involving low-frequency components.

Removing outliers in EEG signals involved calculating the Z-score for each data point and then applying a threshold to identify and remove outliers. Outliers are said to be present if the absolute value of the Z-score exceeds a threshold of ±3. The threshold condition is expressed as in Eq (1)

$$\left| \frac{X - \mu}{\sigma} \right| > 3 \tag{1}$$

where X is the data point, μ is the mean, and σ is the standard deviation.

2) min-max normalization method: The min-max normalization method is advantageous in high-dimensional data. The values for EEG signals are measured in micro-volts and can vary significantly between different channels [11] and across the people. Min-max normalization is used to scale the EEG signals to a fixed span of values before applying it to the CNN model facilitating faster convergence [8]. In this study, the signal values were scaled to the range [0,1], ensuring different features contribute equally to the analysis. The expression for min-max normalization is:

$$\text{Normalized Value} = \frac{X - \min}{\max - \min} \tag{2}$$

where X is the original value, min is the minimum value of each EEG channel, and max is the maximum value of each EEG channel.

3) Filtering: The artifacts in EEG data are primarily caused by physiological fluctuations such as heart rate and respiration, movement artifacts like eye blinks and head shifts, and equipment drift. These artifacts tend to introduce slow, oscillatory unwanted signals that interfere with the EEG frequency range, potentially distorting the original signal. A high-pass filter with a threshold frequency of 0.5 Hz was used to obtain 0.5 Hz to 512 Hz band-limited signals to preserve all frequency components relevant to cognitive tasks. Power-line interferences were removed using notch filters at 50 Hz and its harmonic frequencies ensuring the EEG signals accurately reflect the underlying neural processes [12].

The removal of the low-frequency noise and electrical noise results in EEG data without any noise. This cleaned EEG data is now suitable for subsequent analysis and was utilized by the proposed deep learning algorithm to extract meaningful features automatically for classification.

4) Segmentation: Segmentation involves dividing continuous signal data into smaller segments, which helps to capture and analyze localized EEG patterns. This process is essential for time-series data, where different segments may exhibit distinct features or behaviors relevant to the task. In this study, the segmentation of the processed EEG was facilitated by utilizing annotations that marked specific events within the data. Each 20 s segment overlaps with 10 s previous window resulting in a total of 1576960 × 19 sampling points per participant, which increases the size of the dataset significantly, making it suitable for deep learning models.

B. Deep Learning Algorithm

Deep learning uses neural networks with multiple layers to learn complex patterns in data [7]. Unlike conventional machine learning methods, the deep learning algorithm performs both feature extraction and classification automatically. In this study, a deep one-dimensional CNN model has been deployed to differentiate the frequent and infrequent readers.

1) Convolutional Neural Network: CNNs are a class of deep-learning network that extracts high-level features automatically from raw input. Each neuron in a CNN has an activation function, a mathematical function that introduces a non-linearity and converts weighted inputs into outputs. CNNs consist of three main layers: the convolutional layer, the pooling layer, and a fully connected layer [1]. CNN models are generally used to recognize two-dimensional (2D) images [6]. One-dimensional (1D) EEG signals can be converted to 2D data by plotting spectrograms or topographical mapping which is a much more powerful image representation. However, this demands increased computational complexity requiring more data for higher performance. Hence, this study employs 1D CNNs using 1D signals directly, reducing the computational complexity and enabling real-time classification. [9].

2) Proposed CNN architecture: The proposed CNN model handles sequential EEG signal data, with a shape of 1,576,960 time steps and 19 features per step. The proposed model consists of twenty-four layers, optimized for capturing spatial and temporal dynamics of the EEG signal. The choice of an increasing number of filters (32, 64, 128, 256, and 512) throughout the convolutional layers is to capture more complex features progressively. By starting with 32 filters, the model learns basic local temporal dependencies without enormous computational resources. As the depth increases, higher-level features, and more abstract representations are captured, justifying larger filter sizes in later layers. A kernel size of 3 was selected to effectively capture local temporal dependencies in the EEG data while keeping computational complexity manageable. This kernel size is apt to detect short-term fluctuations in the signal, which are crucial for analyzing brain activity. BatchNormalization was included after each convolutional layer to normalize the layer outputs, which helped stable and faster training, allowing the model to converge faster. The LeakyReLU activation function was used to ensure better learning. MaxPooling1D, with a pool size of 2, was used after each convolutional layer to reduce dimensionality and computational load. This pooling also helps prevent overfitting by focusing on the most salient features from the convolutional layers. After deeper convolutional layers, GlobalAveragePooling1D was employed to further lower the spatial dimensions within the feature maps by averaging them, ensuring that small yet relevant details are retained for classification. Dropout layers with a rate of 0.5 were applied after certain convolutional layers to reduce overfitting. By randomly setting 50% neurons as inactive during training, these layers prevent the model from relying too heavily on specific neurons, encouraging it to learn more generalized and

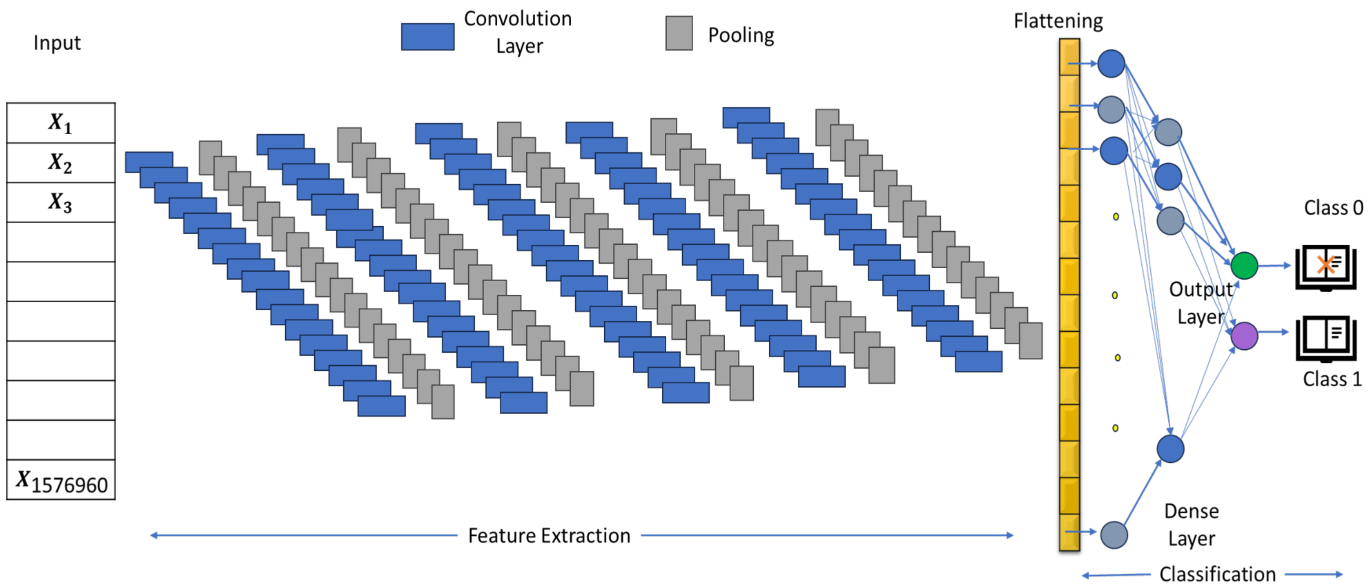

Fig. 4: Proposed CNN architecture

robust features from the data, thus minimizing the risk of overfitting. After the final convolutional and pooling layers, two dense layers with 512 and 256 units, were used to refine the learned feature representations. Before the network reaches the output layer, these deep layers enable it to capture intricate correlations between features. The final output layer contained a single neuron with a sigmoid activation function, suited for binary classification, determining whether the input data corresponds to a frequent or infrequent reader. The CNN model was optimized using the Stochastic Gradient Descent (SGD) optimizer with a learning rate and momentum of 0.01 and 0.9 respectively. This choice balanced the speed of convergence and prevented overshooting during training. The binary cross-entropy loss function was employed to optimize classification accuracy, a standard approach for binary classification tasks. This CNN architecture was optimized through an iterative process, where different CNN model parameters and activation functions were tested. This approach ensured that the final model is best suited for capturing complex temporal and spatial patterns of EEG data, maximizing performance while minimizing overfitting. The proposed CNN model architecture is shown in Fig.4.

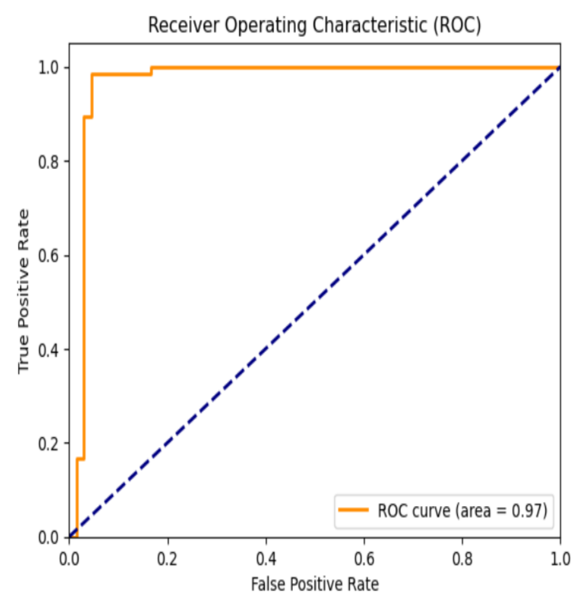

Fig. 5: Receiver Operating Characteristic Curve

IV. Results

The 1D CNN model, composed of 24 layers, was employed to classify EEG signals into frequent and infrequent readers. The model was trained and tested on an EEG dataset comprising 9 participants performing tasks related to antonyms, synonyms, analogy, and passage reading. The final model achieved a classification accuracy of 93.94 %, demonstrating its effectiveness in distinguishing between frequent and infrequent readers based on EEG data. The model was assessed using the Receiver Operating Characteristic (ROC) curve. The model displayed an area under the curve (AUC) of 0.97 during the ROC curve analysis, indicating a desirable level of discrimination between the two classes. Fig 5 displays the ROC curve which compares the true positive rate (sensitivity) against the false positive rate (1-specificity). This high AUC value enhances the model's potential to discriminate and classify frequent and infrequent readers using EEG data.

V. Discussion

This study presents a CNN model for classifying frequent and infrequent readers based on EEG signals, achieving a classification accuracy of 93.94%

This study focuses on a CNN model due to its robust feature extraction capabilities from EEG signals, without requiring hand-crafted features. CNNs are ideal for complex data like EEG. Although this study doesn't directly compare the performance of the proposed model with traditional machine learning models, CNN's results strongly support the focus on a deep learning approach. Future research could include a comparative study with the conventional classification models employing hand-crafted features turning the black box model into a white box.

In summary, the CNN-based model achieved a high classification accuracy, highlighting its potential as a reliable tool for EEG-based cognitive assessment. These findings contribute to the growing body of research supporting deep learning approaches in EEG analysis, with implications for applications in automated classification, cognitive profiling, and neuropsychological research.

VI. CONCLUSION

Reading involves multiple cognitive processes and different brain regions. The neural activity of frequent and infrequent readers differs. This study used EEG signals collected during language tasks to classify frequent and infrequent readers. A twenty-four-layered 1D CNN model was employed for the classification. The results suggest that EEG-based assessments can be used to develop personalized educational assistance for identifying infrequent readers and improving their reading skills. This model can also identify potential reading difficulties early, aiding in designing early interventions for dyslexia or other learning disabilities. Future research could explore incorporating additional tasks, optimizing model architectures, and validating results on larger datasets to enhance generalizability and reliability, making the models more interpretable for practical applications.

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