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Early Identification of Parkinson's Disease Using Time Frequency Analysis on EEG Signals

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Abstract - Parkinson's Disease (PD) is a progressive neurological disorder. It affects movement and can significantly impact quality of life. Early and accurate diagnosis is crucial for effective management and intervention. Traditional diagnostic methods can be time-consuming and less effective in the early stages of the disease. This study aims to develop an automated approach for identifying PD using time-frequency image analysis of electroencephalogram (EEG) signals. The goal is to enhance diagnostic accuracy and efficiency, facilitating early detection. EEG signals, often contaminated with artifacts such as eye blinks and muscle movements etc., were first cleaned. Time-frequency images were then plotted from the cleaned signals, and Event-Related Spectral Perturbation (ERSP) plots were extracted. A customized deep learning model was employed to classify the ERSP plots, distinguishing PD patients from healthy controls. The deep learning model achieved an accuracy of 94.64% in separating PD patients from healthy controls. The approach demonstrated robustness against common EEG artifacts, ensuring reliable PD detection. The model's architecture was specifically designed to handle the complexities of EEG data, making it a powerful tool for PD classifications. This study highlights the potential of integrating deep learning with EEG analysis to explore PD diagnosis. The proposed method is faster and more accurate than traditional approaches, enabling early detection and timely intervention. By reducing the time required for analysis and enhancing diagnostic accuracy, this approach can significantly improve patient outcomes and support better management of Parkinson's Disease.

Keywords— Event-Related Spectral Perturbation, Electroencephalogram, Parkinson's Disease, Time Frequency Representation, EEG Signal Processing and Analysis

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1. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder. Millions of people are affected by this condition [1]. There are two types of symptoms of this disease. Motor symptoms are bradykinesia, rigidity, resting tremor. Non-motor symptoms are anxiety and depression [2]. This condition significantly impairs quality of life. The nervous system affected by this condition first. Then slowly parts of the body controlled by these nerves gets affected. The most common symptoms result from the loss of neurons in an area near the base of the brain. It is called the substantia nigra [3]. Early and accurate treatment is critical for effective management and treatment. Researchers have identified

signs of Parkinson's disease in the brain. The changes will start 15 to 20 years before the symptoms appear [4]. Pre-clinical identification of PD is not easy, patients with very early PD may not meet the clinical diagnosis criteria [5]. Currently, early identification of PD is done using Genetic Testing, biomarkers like alpha-synuclein detection in the brain, imaging techniques i.e. PET Scans [6]. Usually, these diagnostic techniques are very expensive and time consuming whereas electroencephalography (EEG) is cheap and easily available in normal clinical setting.

In this study, we have used a deep learning framework using time frequency component images generated from EEG signals from PD patients and matching controls. To conduct this study, the dataset has been obtained from University of Iowa (UI) in USA. This dataset consists of EEG recordings from 33 individuals with PD and 33 healthy control subjects. EEG works by capturing the brain's electrical activity, specifically from the pyramidal neurons in the cerebral cortex [7]. This method is non-invasive, doesn't require any surgical procedures. Its high temporal resolution can capture brain activity changes very quickly. It also has high reproducibility. Thus, it consistently produces reliable results even when external conditions change. This makes EEG useful for clinical use and research, especially in diagnosing PD. The EEG recording is broken down into time and frequency parts and represented it into images. These images represent complex patterns and time changes that linked to PD-related brain activity. We used these images as inputs for a deep learning neural network (DL).

A deep learning (DL) model is introduced to conduct this study. DL can detect complex EEG signals patterns. The complete architecture is explained in the methodology section. The architecture of the DL model is designed such way that it can extract the abstract features from the input images. It will enable the model to learn the complex differences between PD patients and healthy control's EEG recordings. The first few layers of the DL model will focus on extracting edges and textures. The later layers will learn more complex, high-level features that are relevant for PD classification. Our aim is to classify PD patients from EEG signals accurately by tuning the correct parameters of the model. Our goal is to use component time frequency image as input in the DL framework which can identify PD in the early stage even before the symptoms appear.

2. LITERATURE REVIEW

2.1 Parkinson's Disease

PD is a neurological movement disorder. It becomes more critical over the time. People may begin to notice the problems with movement when the nerve cells or neurons in certain parts of the brain weaken, damaged or die. The common symptoms are tremor, slowed movement (known as bradykinesia), rigid muscles, impaired posture and balance, loss of automatic movements and in some cases speech and writing changes. While symptoms progress over the time, people may have difficulty walking, talking or completing simple tasks. The most two of the common causes of PD are genetic changes and exposure to specific toxins or ecological elements [8]. The first neural changes start from the loss of neurons in an area near the base of the brain and it is called the substantia nigra [9].

There are several tools available to help diagnose PD. One of them is imaging techniques like Single-photon emission computed tomography (SPECT). Another one is Cardiac 123I-metaiodobenzylguanidine (123I-MIBG) which can reveal changes in the brain related to PD. It can reveal how the brain's dopamine-producing neurons are affected [10]. Existing methods to diagnose PD such as Blood and Imaging Tests, Dopamine Transporter (DAT) Scan, Tests for Alpha-Synuclein Proteins, and Medication Trials. These methods are helpful but have some limitations. Firstly, these methods may oversimplify complicated decisions and possible to miss important details in some cases. Secondly, an accurate diagnosis is expensive most of the times and these methods may not be flexible enough because of following the pre-determined steps without considering each patient's specific needs [11].

The alpha synuclein biomarker has emerged as a significant diagnostic tool for PD. This protein, normally found in the nervous system, becomes abnormal in PD patients. Cluster of misfolded alpha synuclein that accumulates in neurons and it contributes to the disease's progression [12]. Early identification of these abnormalities can allow for better management and targeted therapies. EEG has emerged as a promising tool for assessing PD. Many researchers have explored EEG microstates in PD patients. Most of the cases which represent distinct patterns of neuronal activity during the rest. These microstates have the potentials to be used as markers for PD [13]. For example, less occurrences of Map1 (a prototype microstate) might suggest PD, with or without dementia [14]. Also, a recent study showed that EEG markers are strongly linked to the MDS-UPDRS score, a scale for measuring PD symptoms [15].

This study focuses on using EEG signals and represent it as a time frequency image and CNN to create an accurate model for PD classification. EEG gives a non-invasive way to capture the complex changes to study the brain activity related to PD. CNNs are well-known for finding complex patterns in high-dimensional data. It makes them useful for analyzing the brain activity. The aim of this study is to help improve early diagnosis and monitoring of PD by combining time frequency and CNN. This study builds on past studies by solving the problems of older PD classification methods by exploring on how CNNs can find important features in EEG data.

2.2 EEG Signal and Time Frequency Analysis

EEG works by placing small sensors on the scalp of the head. These sensors are able to detect tiny electrical signals made by neurons when they are active. The signals can be represented in a larger way and displayed on a screen to give a live view of brain activity. EEG signals come from the combined activity of many neurons working together [16]. There are 5 different brain waves which are delta, theta, alpha, beta, and gamma. They are linked to different brain functions and states. For example, delta waves are available in during deep sleep, beta waves are linked to being awake and focused. Analyzing the features of these EEG frequency bands is very important. It can provide important information for diagnosing brain problems like epilepsy, sleep issues, and other brain-related medical conditions. Previous study has shown that the gamma band (30-100 Hz) proved to be the best features useful for early PD diagnosis and treatment [17].

EEG is proved to be very useful for finding and tracking brain disorders. In epilepsy, EEG can be used to find abnormal brain activity that causes seizures [18]. For Alzheimer's disease, EEG shows the change of the brain wave that is linked to memory loss [19]. PD also has unique EEG patterns. A recent study shows that PD patients often show changes in the beta and alpha bands especially the increased beta activity in the front and middle parts of the brain which is common [20]. Alpha wave strength and frequency are often lower and it can show the changes in brain alertness and thinking abilities using EEG. These EEG features are very important to understand PD's brain mechanisms and improve its diagnosis and treatment.

EEG signals analysis is complicated because of two main reasons. The first one is the low signal-to-noise ratio, and the other one is the random nature of EEG. These signals are mostly mixed with noise, artifacts, muscle movements, and eye blinks. These noises can cover the real brain activity. Preprocessing is very important before analyzing the data. However, there are no specific methods to clean the signal. It makes the process a bit risky. This is because during cleaning, there is a possibility to remove important parts of the signal. It may affect the final results. The random nature of EEG signals adds another layer of complication. Automated methods are available which study the nonlinear dynamics. It can provide the useful information, but it will take a lot of time and computing power. There are different ways to analyze EEG signals. One of them is called Event-Related Potentials (ERPs) representation. Another popular method is called Fourier-based power analyses. These methods can help understand psychological processes. ERPs study focuses on how the brain responds to events or stimuli over time [22]. Fourier-based power analysis represents at how different parts of the EEG signal's frequencies explain the brain activity [23]. Both methods are useful in learning how the brain works. However, these methods do not fully use the important information in EEG signals. ERPs are based on the brain’s response to an event that happens at the same time across many tests which means ERPs only analyze the activity that matches the events’ timing. It also ignores brain activity that does not perform the similar. There is a possibility that it can miss the useful information from signals that are not perfectly aligned during tests [24]. Fourier-based power analysis only focuses on the signal’s frequency, not considering how brain activity changes over time [25]. These methods are unable to capture the complexity of EEG data. This may lead to miss the important information unrelated to specific events or fixed frequencies.

Time-frequency analysis is an important method to represent the signal over time. It represents how the frequency of EEG signals changes over time. Time-frequency methods allow analysis of both time and frequency at the same time [26], which Fourier analysis cannot perform. It shows the spectral features that changes during certain events or conditions. For example, when studying event-related EEG oscillations, researchers separate EEG signals into magnitude and phase information for each frequency [27]. This method shows the changes over time (in milliseconds) which related to task events [28]. Some of the common methods are the Short-Time Fourier Transform (STFT), which breaks the signal into overlapping sections and does Fourier analysis on each section [29]. Another one is the Wavelet Transform (WT). It uses scalable functions to study different frequency components at various times [30]. There is also the Wigner-Ville Distribution. It provides a detailed time-frequency picture but can suffer from interference terms

[31]. These methods give important insights into brain activity's dynamic nature and help researchers study things like event-related potentials and brain rhythms.

Time-frequency representations (TFRs) give a better view of EEG data by capturing both time and frequency information. It allows the researcher to study on how brain signals change over time. It provides the useful insights into brain activity's dynamics. Time-frequency analysis helps find changes in brain rhythms. For example, the beta band is higher in PD patients [32] compare to healthy controls. This activity is observed in the brain's front and middle areas [33] and has a higher strength and frequency compared to healthy people. Recent study shows that PD patients may have lower alpha wave strength and frequency [34]. This suggests the changes in brain alertness and thinking ability. By analyzing the time-frequency feature, researchers can differentiate PD patients apart from healthy individuals. It can also contribute to understand the disease's brain mechanisms and improving its diagnosis and care. Though time-frequency representations can help to understand the abnormalities better, it also has challenges. It requires high computational resources, especially with big datasets and advanced methods like the Wigner-Ville Distribution. EEG signals are naturally contaminated with artifacts. The choice of the cleaning method can affect how well it handles noise. It is important to pick the right method for the research goal to get the best results. Factors like the time and frequency, computing efficiency, and noise resistance can be very useful to guide the choice of time-frequency analysis method. Time-frequency analysis is very important in our study for CNN-based classification. By capturing both time and frequency information, it can identify the small changes in brain activity linked to PD. This feature can improve the accuracy and strength of our classification model. In this study, we have employed the wavelet-based method to create the time-frequency image with the aim to capture EEG signal parts that may provide better features for classifying PD.

2.3 Deep Learning

Deep learning uses neural networks with many layers to process complex data. It is able to learn patterns and features from complex data. Deep learning models can work with large and complicated datasets. It can automatically find features in the data. It is very useful for image recognition, NLP, and speech recognition. It can identify the patterns directly from raw data without the need for excessive amount of code. It can identify complex patterns and relationships that human might miss. Deep learning has contributed greatly in the areas of computer vision, healthcare, and finance. There are many different types of deep learning models. Some of the popular ones are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Generative Adversarial Networks (GANs), and others.

CNNs are one type of deep learning model. It is very useful for grid-like data as images. CNNs are consist of layers like convolutional layers, pooling layers, and fully connected layers. Convolutional layers capture the features from the input image. Pooling layers reduce the size of feature maps. Fully connected layers combine the features to make the final prediction [35]. CNNs are very good at finding patterns and recognizing features, which makes them great for analyzing images, such as diagnosing medical images or segmenting them.

Binary classification is a type of supervised learning where the aim is to predict one of two possible outcomes for a given input. For Parkinson's Disease (PD), binary classification helps to distinguish PD patients from healthy individuals. CNNs are commonly used for binary classification tasks involving image data. The architecture employs convolutional layers to extract features, pooling layers to reduce dimensionality, and a fully connected layer with an activation function to generate class probabilities [36]. Softmax activation is a standard technique for multi-class classification problems. It assigns a probability to each class [37]. However, for binary classification, the sigmoid activation function is typically used [38]. The sigmoid function is a nonlinear activation function that outputs values in the unit interval. Choosing the appropriate loss function and optimization technique is crucial for effective training and achieving high classification accuracy. Binary cross-entropy loss is a standard loss function for binary classification tasks. It quantifies the discrepancy between predicted probabilities and ground truth labels. By minimizing this loss, the model is trained to produce accurate predictions. Optimization algorithms like stochastic gradient descent (SGD) and its variants (e.g., Adam, RMSprop) are employed to update the model's parameters iteratively. These algorithms adjust the weights and biases of the CNN to minimize the loss function, thereby enhancing classification performance. Some of the popular deep learning model for binary classification are Logistic Regression, RNN and LSTM, Fully Connected Neural Networks (FCNNs), Support Vector Machines (SVMs), Autoencoders etc [39]. But CNN outperformed among all other deep learning models when it comes to image classification [40].

CNNs have proven effective for EEG signal classification by feeding time-frequency images as if they were traditional images. This approach allows CNNs to automatically learn discriminative features from the spatiotemporal patterns in EEG data. However, EEG-based CNN classification faces unique challenges. EEG signals exhibit significant variability across subjects and even within the same subject across different sessions [41]. This variation can make it hard for CNNs to work well with new data. Strong feature extraction methods are needed to solve this issue and ensure the classification is accurate. By carefully choosing the suitable preprocessing pipeline and feature selection steps, CNNs can provide the best classification accuracy which can be helpful to understand the brain activity and the neurological disorders.

CNNs are useful for classifying PD because it can find small patterns and features in time-frequency EEG images. These features consist of the signs of PD. It is hard to identify using traditional machine learning methods. CNNs able to learn the complex features directly from EEG data [42] which leads to better classification accuracy and reliability. Training CNNs for binary classification has some problems. The common problem is called overfitting. It happens when the model remembers the training data instead of learning general patterns. It performs poorly on new data especially when the dataset is small. Some methods can be very useful to avoid overfitting. The popular methods are data augmentation, transfer learning, and regularization. Data augmentation can make the dataset larger. It will apply changes like rotation, scaling, adding noise, and time warping which increases the variety in the data. It helps the model generalize better. Transfer learning uses the pre-trained models from large datasets. An example of this is ImageNet. It makes training faster and improves results. Regularization methods are also useful in deep learning. Methods like dropout and L1/L2 regularization help reduce overfitting. Dropout turns off some neurons randomly during training which will cause stopping them from relying on each other. L1/L2 regularization adds a sanction to the loss function. It will encourage smaller or more selective weights to limit overfitting. CNNs can work well for PD classification by applying these methods. It will offer a strong method for better diagnosis and early treatment.

CNNs were chosen because they are very good at finding complex features in image data. This makes them suitable for binary classification tasks like time-frequency EEG images. CNNs are suitable for this task because they can automatically learn multi-level representations from input data. They find subtle patterns and features that could indicate Parkinson's Disease (PD). By using CNNs, we aim to create a highly accurate and reliable model to help diagnose and manage PD early. To improve classification even more, we are trying out new CNN designs and improvements. We are also adding attention mechanisms to our CNN design. This focuses on the most important parts of the time-frequency images, which might improve both accuracy and understanding of the results. By using these advanced methods, we believe our CNN-based solution will make an important contribution to PD classification.

2.3 Related Works

Many studies have looked at how time-frequency analysis and deep learning can help detect PD early using EEG signals. Ruilin Zhang, Jian Jia, and Rui Zhang proposed the Tunable Q-factor Wavelet Transform with Deep Residual Shrinkage Network (TQWT-DRSN) and the Wavelet Packet Transform with Deep Residual Shrinkage Network (WPT-DRSN) to classify different clinical sleep EEG data. These included PD, REM sleep disorder, PD with REM sleep disorder, and a control group [43]. These models work well for diagnosing PD because they can capture the complex patterns and time-related changes in EEG signals. The TQWT-DRSN and WPT-DRSN models successfully extracted useful features from the EEG data. This led to better results compared to other methods. These models reached high accuracies of 99.92%, 97.81%, and 92.59% for 2-class, 3-class, and 4-class classification tasks, respectively. Oh and Hagiwara used a CNN to diagnose PD from EEG signals and achieved an accuracy of 88.25% [44]. Shaban and Amara created a 20-layer CNN applied to the wavelet domain of resting-state EEG, achieving very high accuracy [45]. Siuly and her team introduced a Wavelet Scattering Transform (WST)-based AlexNet CNN model to diagnose PD from EEG data and reached an accuracy of 99.84% [46]. Yang and Huang used support vector machines (SVM) and CNNs for classifying PD with resting-state EEG, showing excellent accuracy [47]. Xu used a pooling-based deep recurrent neural network (PDRNN) to detect PD from EEG signals, achieving an accuracy of 91.81% [48]. These studies together show how time-frequency analysis and deep learning can help identify PD early, offering useful ideas for future research and medical use.

Our method for classifying PD using time-frequency analysis stands out from current approaches because it is simple and effective. By using component time-frequency analysis to create time-frequency plots, we rely on a well-known technique. This method can capture the detailed temporal and spectral features of EEG data. In addition, carefully cleaning and preprocessing the data ensures the results are accurate and reliable. We use a straightforward CNN design

with several convolutional, pooling, and dropout layers. This creates a strong and easy-to-understand model. This straightforward design facilitates implementation and understanding, while still achieving competitive performance. In contrast to more complex models that may introduce additional computational overhead and challenges in interpretability, my approach offers a practical and efficient solution for early PD detection.

3. RESEARCH METHODOLOGY

3.1 Dataset

This EEG signal data has been collected by Narayanan Lab from University of Iowa [49]. It is a publicly available dataset. The dataset consists of EEG recordings from 33 PD patients and 33 healthy control participants. These EEG signals were acquired during resting-state conditions where participants were not actively performing any specific tasks. Resting-state EEG captures spontaneous brain activity and provides insights into neural connectivity patterns. Each EEG recording utilizes 63 electrodes to capture brain activity. The data is sampled at a rate of 500Hz. In total, there are 1,758 epochs, with each epoch containing 1,500 frames of data. These epochs span from -1000ms to 1998ms, covering a significant period around the event of interest. Across all recordings, there are 10,132 distinct events, providing a rich dataset for analysis.

3.1 Approach

This study has been conducted into 2 sections. First one is the EEG signals processing to generate the time frequency image and the second one is building the deep learning neural network framework.

3.1.1 EEG Signal Processing Methodology

Figure 1 demonstrates the methodology diagram of the first part of this research which is the EEG signal processing. A toolbox from Matlab (version R2022b) called EEGLAB (version v2022.1) is used to analyze the signals.

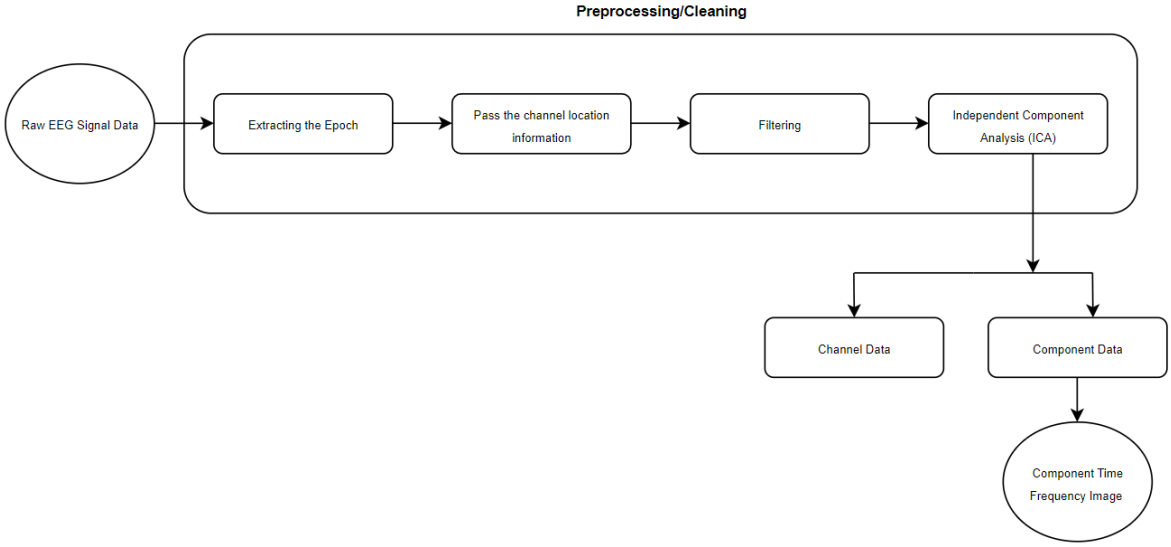

Figure 1. EEG Signal Methodology

The main challenge of this section is to preprocess and clean the data carefully so that the important information from signal will not be eliminated. The initial move is to load the EEG data in EEGLAB. The EEG signal data format is '.eeg'. It is Nihon Kohden brainvision EEG data. This data is imported in EEGLAB as EDF/EDF+/GDF files. After importing the data, the preprocessing and cleaning part starts with extracting the epoch. As previously mentioned in

the dataset information that the total number of electrodes are 63 which means there are 63 channels. But the channel location information was missing from the data and had to be manually provided. The next step is to filter the data. Using basic FIR filter method from EEGLAB, the low passband is set to 0.5Hz and the high passband is set to 50Hz. This filtering has been done because the selected frequencies will improve the overall signal-to-noise ratio (SNR). Also, the higher frequency band will take an enormous amount of time to complete next step which is ICA. ICA stands for Independent Component Analysis. It will remove artifacts embedded in the signal (example muscle movement, eye blinks or eye movements etc.) without removing the affected data portions. It is one of the most important steps in EEG signal processing. It is also a time-consuming process. Following the completion of ICA, two types of images can be visualized which is the channel data and the component data. This research focuses on component activity. ICA will separate all the activity into different components that has been captured during the recording. These components heavily rely on the number of channels/electrodes. If the number of electrodes is 128, the process will generate 128 components. In this research, our data recorded with 63 electrodes, meaning 63 components has been generated.

Figure 2 is an example of a time frequency component image. It demonstrates the first time-frequency component image that is generated from the EEG recording of Subject 1 PD patients. Figure 2 shows how the power or amplitude of a component's activity changes over time and across different frequency bands. Two plots are visible in Figure 2, the first plot is ERSP (event-related spectral perturbation) and the second plot is ITC (inter-trial coherence). We are only interested in the ERSP plots. For this reason, ITC plots has been removed. These images will be used for deep learning purposes. So, the axes and the indicators along with the whitespace of the image will not be needed. For this reason, the only important part of the image will be cropped out.

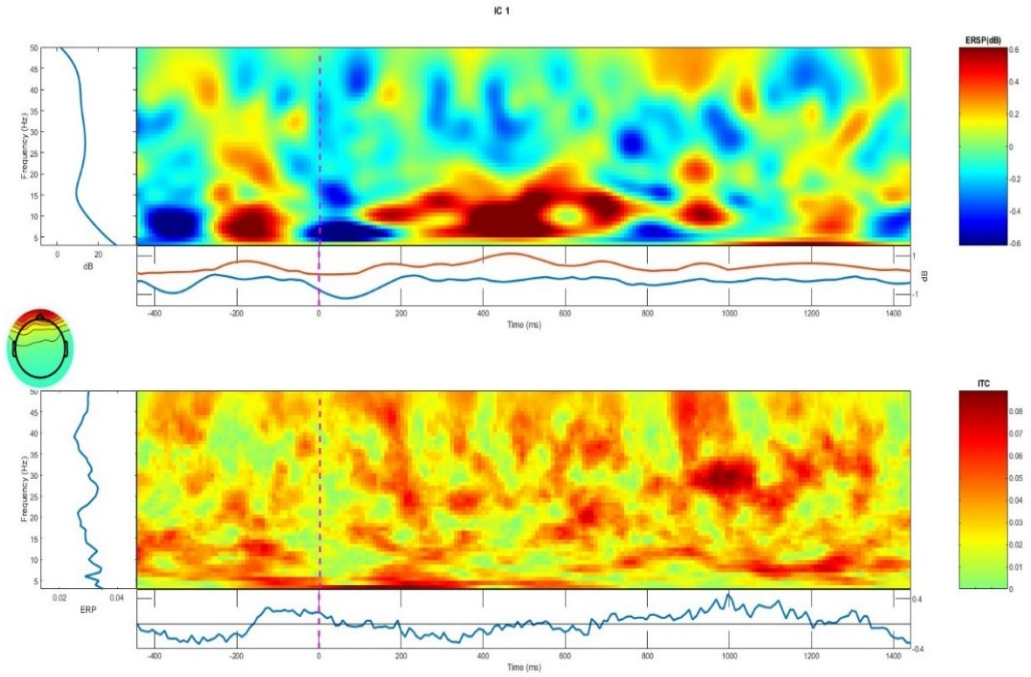

Figure 2. Time Frequency Component Image

Figure 3 shows the final output of the image. This image size is 500 x 400 pixels. The total number of subjects are 74 (PD 37 + Control 37). From each Subject, 63 time-frequency component images will be generated. For the deep learning classification, the total number of images will be 4662 (Total subjects 74 x 63 time-frequency component images).

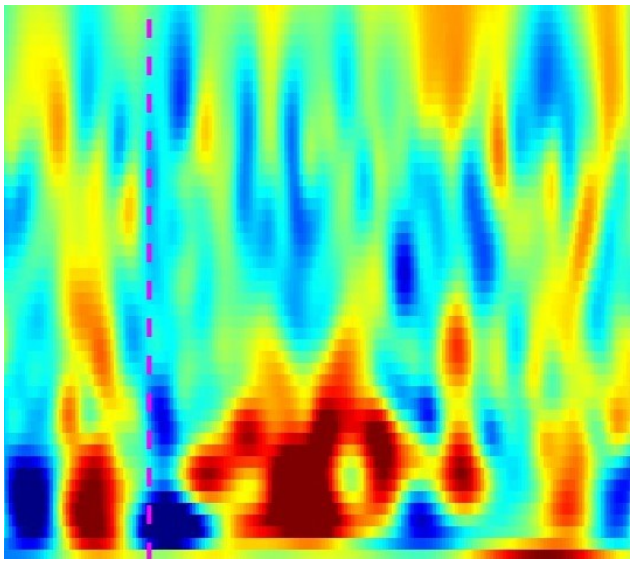

Figure 3. Preprocessed TF Component Image

3.1.2 Deep Learning Methodology

Jupyter Notebook is used to conduct this section. The specifications of the computer that is used for this study is as follows – Windows 10 Pro 64-bit operating system, Intel(R) Core (TM) i5-8400 CPU @ 2.80GHz 2.81 GHz, 32 GB RAM, RTX 2080ti GPU. A customized CNN model is used to conduct this study with PyTorch framework. The image preprocessing is done using OpenCV. Figure 4 demonstrates the diagram of the second part of this study which is the steps of deep learning methodology.

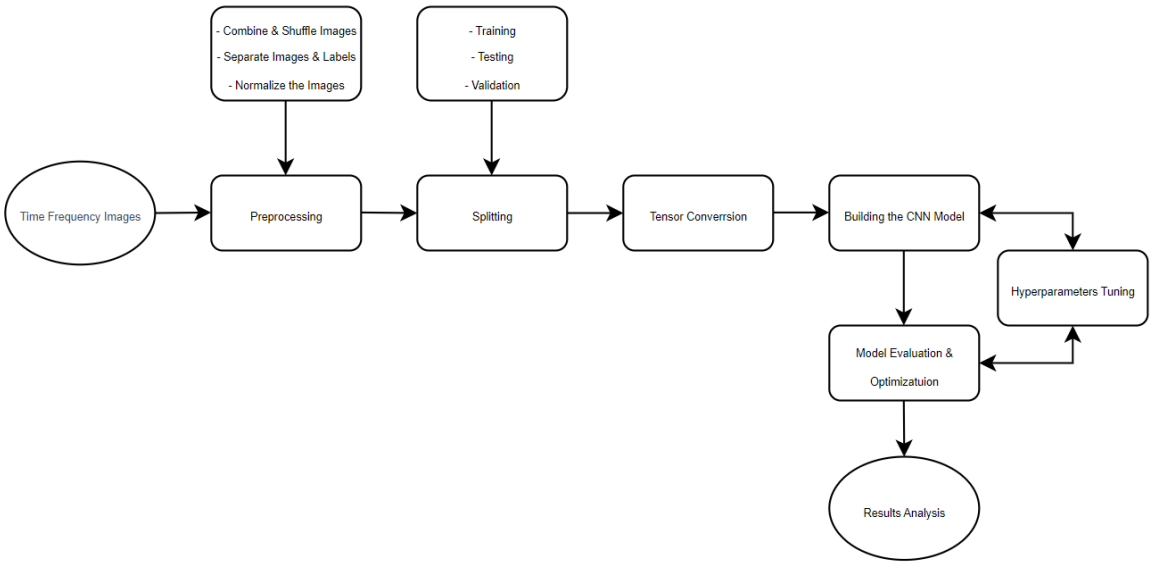

Figure 4. DL Methodology

The deep learning methodology begins by importing key libraries such as NumPy, OpenCV, scikit-learn, and PyTorch within a Jupyter Notebook kernel. These libraries facilitate the various steps of data handling, image processing, and model training.

The workflow starts by loading time-frequency images generated from EEG signals, which are categorized into two classes: PD and Control. These images are stored in two separate folders and are then loaded using OpenCV.

In the next step, data preprocessing is carried out. First, the images from both classes are combined into one dataset. This step is necessary for the binary classification task. The combined dataset is shuffled to make it random. This prevents the model from learning patterns related to the order of the data. After that, the dataset is split into features (X) and labels (y). Here, X represents the image data, and y represents the class labels. Both images and labels are converted into NumPy arrays to make processing faster and easier. The pixel values of the images are scaled between 0 and 1. This normalization helps avoid numerical problems during training. The dataset is then divided into training, validation, and testing subsets. With a total of 4662 time-frequency images, 60% (2797 images) is used for training, 28% (1304 images) for validation, and 12% (560 images) for testing. This division ensures the model is trained and tested properly, reducing the chance of overfitting.

Next, DataLoader objects are created for the training and validation datasets. The training DataLoader shuffles the data in every epoch. This ensures that training batches are diverse. The validation DataLoader, however, keeps the original order to give consistent evaluation results. DataLoader objects make batch processing during training and evaluation faster and more efficient.

The CNN architecture is then built. Details of the architecture are discussed later in the study. Hyperparameter tuning is important here. The batch size is set to 32 to prevent memory issues. The number of epochs is set to 20, meaning the model will go through the training dataset 20 times. The learning rate is set to 0.001. This value helps the model learn gradually without overshooting the optimal weights. The input images are resized to 500x400 pixels to match the size expected by the model.

The training and validation process uses PyTorch and GPU acceleration, which greatly reduces the time needed for training. After training is complete, the model's performance is tested on the test data. Metrics such as test accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and precision-recall curve are calculated to evaluate the model. These results are fully analyzed in the Results and Discussions section.

3.1.3 Customized CNN Architecture

A customized CNN model is used in this study. This CNN structure is ideal for binary classification because it balances complexity and regularization. Several convolutional layers are used to capture complex features from the input images. Max pooling layers reduce spatial dimensions, which helps keep important features and reduces the computational load. Dropout layers are placed to prevent overfitting by randomly turning off neurons during training. The fully connected layers convert the extracted features into a binary output using a sigmoid activation function.

Figure 5 shows the customized CNN architecture. This architecture begins with two convolutional layers with 32 filters, a kernel size of 5, and padding of 2. This followed by a max-pooling layer which reduces the spatial dimensions by half. A dropout layer with a rate of 0.5 is added after pooling. It will be essential to prevent overfitting. The model then has three more convolutional layers with 64 filters and a kernel size of 3. The next one is another max-pooling layer and a dropout layer with a rate of 0.25. After flattening the output from the last convolutional layer, the model passes the data through a fully connected layer with 64 units. Then another fully connected layer with 1 unit which will produce a single output. A dropout layer with a rate of 0.1 is applied. Lastly, a sigmoid activation function is used for binary classification.

This CNN architecture is a well suited for binary classification in identifying PD from EEG signals. It balances complexity and regularization and ensure that the model captures detailed time-frequency features without overfitting. The multiple convolutional layers with increasing filter sizes allow the network to detect both fine and broad features. It is essential for identifying subtle patterns in EEG data. Max-pooling layers reduce spatial dimensions, keeping key information as well as lowering computational load, making the model scalable and suitable for real-world use. Dropout layers are introduced at key points to keep the model robust with a smaller dataset. Fully connected layers and sigmoid activation ensure the extracted features are mapped to a binary output for accurate classification. This

model will able to capture enough feature complexity while avoiding issues like overfitting. This problem can happen with deeper architectures (such as a 7-layer network). This architecture is well-suited for the binary classification task.

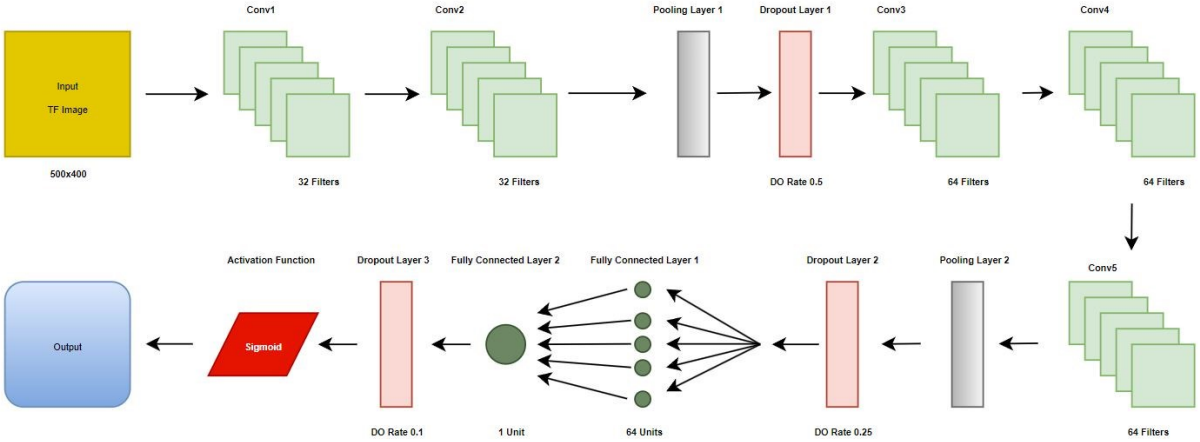

Figure 5. Proposed CNN Architecture

4. RESULTS AND DISCUSSIONS

The results of using Convolutional Neural Networks on EEG time-frequency images for PD classification provides a strong performance. The test accuracy is 94.64% and the test loss is 0.0203. This model performs well in differentiating between PD and healthy control subjects. The precision score is 0.9439. It proves that the model correctly identifies Parkinson's cases with few false positives. The recall score is 0.9505 resulting the model captures most of the actual Parkinson's cases. The F1-Score is 0.9472. The result demonstrates that the model balances precision and recall well, with strong overall performance.

Figure 6 shows the confusion matrix, which breaks down the model's performance in classifying data into two categories which are PD and healthy controls.

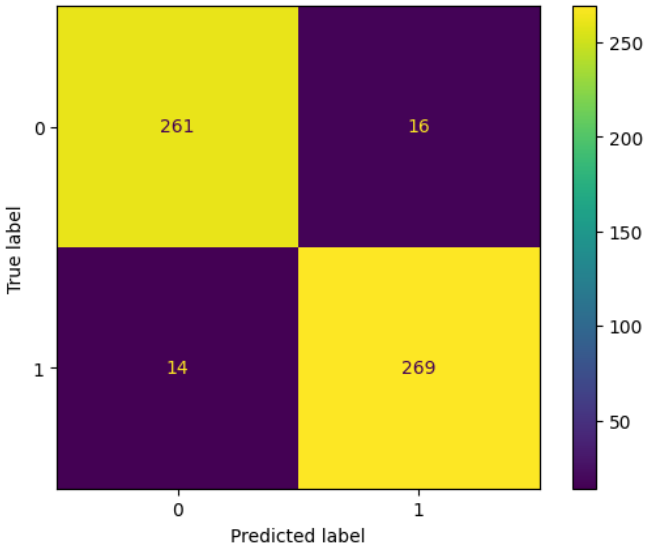

Figure 6. Confusion Matrix of The Studied Method

The matrix demonstrates that the model correctly identified 261 instances with 16 misclassified as positive (class 1) where total of 277 true negative cases (class 0). 269 instances correctly identified out of 283 true positive cases which is class 1 in the matrix. 14 incorrectly classified as negative in class 0. The low number of misclassifications determines the model's reliability in distinguishing between PD and healthy controls, with a low tendency toward false positives. This performance here matches the reported metrics which confirms the model's effectiveness in the classification task.

Figure 7 represents the precision and recall curve of the proposed architecture. It provides a detailed analysis of the model's performance with imbalanced classes. The curve shows that the model achieves high precision across a wide range of recall values. This means that it maintains a low false positive rate while correctly identifying more true positives. The precision starts near at 1.0. It slightly decreases as recall increases. Then drops sharply toward the end of the curve. It suggests that the model performs well with precision above 0.9 until recall becomes very high. Then the precision falls quickly. The average precision (AP) score of 0.97 also supports the model's strong performance. It shows the ability to accurately classify the positive class with minimal trade-off between precision and recall. This high AP score proves that the model is robust and reliable in distinguishing between the two classes, making it ideal for the classification task.

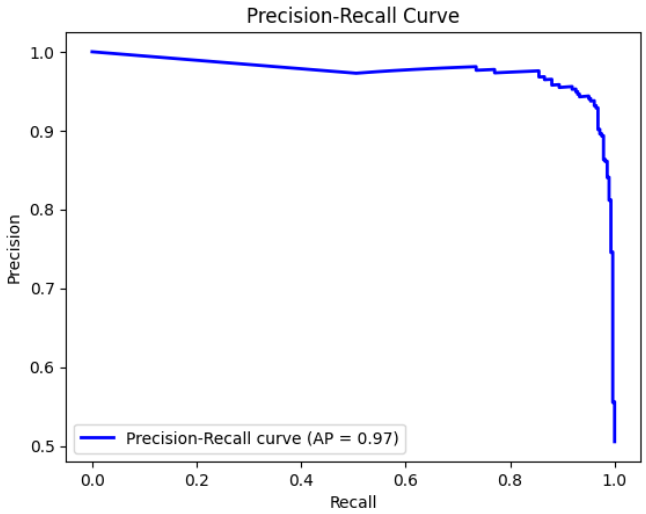

Figure 7. Precision and Recall Curve of the Studied Method

Figure 8 represents the Receiver Operating Characteristic (ROC) curve of the model's performance. The curve plots the true positive rate (sensitivity) against the false positive rate at a different threshold setting. The ROC curve is close to the top left corner. This means the model achieves a high true positive rate while keeping the false positive rate low. This indicates that the model is very useful for differentiating between the PD and healthy controls. The area under the ROC curve (AUC) is 0.98, which is very close to 1.0, showing the model's excellent performance. An AUC of 0.98 means there is a 98% chance the model will correctly identify a positive instance and a negative one. The model's ability to maintain a high true positive rate with only a small increase in the false positive rate shows its robustness and reliability. This result shows that the model is well-calibrated and very good at making accurate predictions for this task.

In comparison to other studies, our model demonstrates competitive performance in classifying PD using EEG data. Achieving a test accuracy of 94.64%, a precision score of 0.9439, and a recall score of 0.9505, my model shows robust classification capability. However, some studies report even higher accuracy. For example, [43]'s use of a deep residual shrinkage network (DRSN) achieved a remarkable 99.92% accuracy in a two-class classification task using EEG sleep data, outperforming our model. Similarly, [46]’s approach, using a Wavelet Scattering Transform (WST) with AlexNet, reached 99.84% accuracy. Although our model does not reach these levels of accuracy, its F1-score of 0.9472 and AUC of 0.98 suggest strong overall performance in balancing precision and recall. Compared to [45], whose CNN-based model achieved 88.25% accuracy, our model performs notably better, underscoring its reliability in this task. Some studies, like Shaban and Amara’s [45] 20-layer CNN, report high accuracy but lack detailed

precision and recall metrics, making a full comparison difficult. While our model performs well, especially in terms of precision, its slightly lower accuracy compared to others may highlight the importance of further dataset expansion or alternative feature extraction methods to achieve optimal results. On the other hand, the proposed CNN model offers several advantages for PD classification. Its five-layer architecture allows for automatic identification of PD using EEG signals without the need for manual feature extraction, selection, and classification. This eliminates the subjectivity and potential biases associated with traditional feature engineering methods. Moreover, the model demonstrates good performance even with a limited number of normal and PD subjects, highlighting its robustness. However, the primary disadvantage of this approach is the limited number of subjects used in its development. A larger dataset would be necessary to further validate the model's generalizability and clinical applicability.

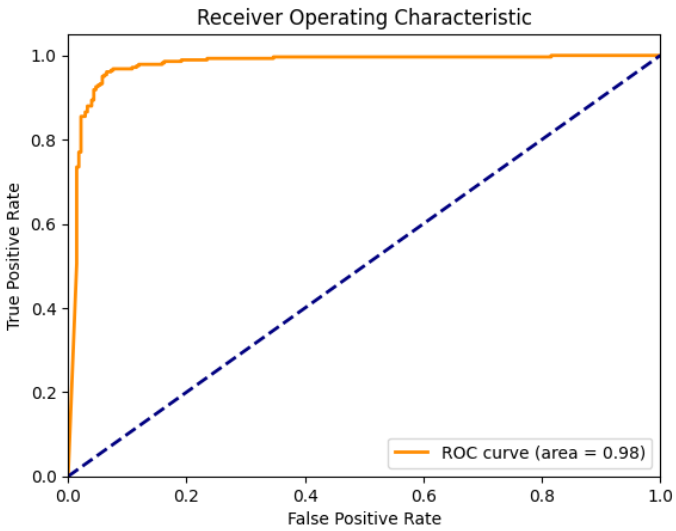

Figure 8. ROC Curve of The Studied Method

5. CONCLUSION

The primary objective of this study was to develop a robust and accurate deep learning framework for the early identification of PD using EEG signals. By extracting time-frequency features from EEG recordings and training a customized CNN model, we achieved an accuracy of 94.64% in differentiating PD patients from healthy controls. This demonstrates the potential of our approach for clinical application, offering a non-invasive screening tool for PD. Future work could explore the integration of other modalities, such as magnetic resonance imaging (MRI) or positron emission tomography (PET), to enhance the diagnostic accuracy and provide a more comprehensive assessment of PD. Also, longitudinal studies could be conducted to evaluate the performance of our model of early identifications of PD and assess its ability to track disease progression. We acknowledge the Narayanan lab for sharing the data publicly.

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Tanvir Hasib: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation
Vijayakumar: Supervision, Writing – Review & Editing.
Ramakrishnan Kannan: Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

The dataset is publicly available and completely anonymized.

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