International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 08 | August - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

NeuroPark: An Automated Approach for Parkinson's Disease Detection

Vinya Bojamma A V[1], Dr. Kavitha K S[2]

[1]PG Student, Dept. of Computer Science & Engineering, Dayananda Sagar College of Engineering, Karnataka, India
[2] Professor, Dept. of Computer Science & Engineering, Dayananda Sagar College of Engineering, Karnataka, India

---

Abstract - Parkinson's disease stands as a pervasive neurodegenerative condition, casting a substantial impact on global health. Swift and precise identification of Parkinson's, in its early stages, holds pivotal importance for efficacious intervention and proficient disease management. Nevertheless, conventional machine learning techniques encounter formidable challenges when deciphering intricate electroencephalogram signals, often necessitating arduous manual interventions. In this research endeavor, we introduce a pioneering methodology for automated Parkinson's detection employing electroencephalogram signals. Our novel approach harnesses Mel spectrogram images, derived from a preprocessed electroencephalogram dataset, seamlessly integrated with convolutional neural networks. This strategic amalgamation enables the extraction of both frequency nuances and temporal patterns from the visual representations, thereby bestowing our model with a remarkable upswing in the accuracy of Parkinson's detection. The methodologies we propose not only hold substantial promise in advancing Parkinson's diagnosis but also bear the potential to foster tailored approaches in the realm of personalized treatment strategies.

Key Words: Parkinson's disease (PD), Classification, Electroencephalogram (EEG), Deep learning, Convolutional Neural Network (CNN), Mel Spectrogram.

1. INTRODUCTION

Parkinson's disease (PD) stands as a prevalent neurodegenerative ailment exerting a substantial global impact. Its hallmark features encompass motor dysfunctions like involuntary tremors, bradykinesia, postural instability, and rigidity, coupled with an array of non-motor manifestations such as depression, olfactory impairment, constipation, and sleep disturbances. Rooted in the depletion of dopamine-producing neurons within the substantia nigra, PD leads to diminished dopamine levels in the crucial motor control hub of the brain, the striatum. The progressive aggregation of misfolded alpha-synuclein proteins within Lewy bodies further fuels the neurodegenerative cascade.

The significance of accurate and early PD detection cannot be overstated, given its potential to pave the way for timely interventions and improved patient outcomes. Presently, the clinical diagnosis of PD hinges on specific criteria encompassing the presence of bradykinesia alongside at least one hallmark feature like rest tremor or rigidity, a positive response to dopaminergic therapy, and the exclusion of specific contraindications. However, the diagnostic reliance on motor symptoms poses considerable challenges, as substantial loss of dopaminergic neurons often occurs prior to the attainment of a clinical diagnosis.

The primary therapeutic strategy for addressing the motor symptoms of Parkinson's disease (PD) revolves around dopamine replacement. Although this approach effectively mitigates motor issues, it does not tackle the underlying neurodegenerative process. This degeneration primarily affects dopaminergic neurons in the substantia nigra, which project to the striatum, and is characterized by the accumulation of misfolded alpha-synuclein proteins forming Lewy bodies.

Fig-1 illustrates that individual with PD experience reduced dopamine transmission across striatal synapses in comparison to their healthy counterparts. Cutting-edge molecular imaging techniques like positron emission tomography (PET) and single-photon emission computed tomography (SPECT) enable the detection of alterations in presynaptic dopaminergic activity when comparing the brains of PD patients and healthy individuals. Despite these advancements, none of the current neuroimaging methods are officially recommended for routine clinical employment in PD cases. Key molecules implicated in dopamine synthesis and transport, such as dopamine transporters (DAT), L-aromatic amino acid decarboxylase (L-AAAD), and vesicular monoamine transporter 2 (VMAT2), are noticeably downregulated in PET and SPECT images, shedding light on the physiological changes associated with the condition.

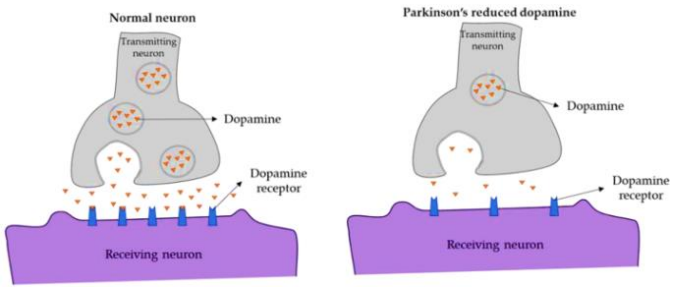

Fig -1: Synaptic terminal in (left) healthy controls and (right) PD patients

The reduction of dopamine transporters, as depicted in Fig- 2 through SPECT imaging, signifies a crucial aspect in understanding Parkinson's disease (PD). Remarkably, the emergence of non-motor symptoms precedes motor symptoms by a considerable span of time, implying the existence of a prodromal or premotor phase. This phase presents a pivotal opportunity for implementing potential neuroprotective interventions with heightened effectiveness.

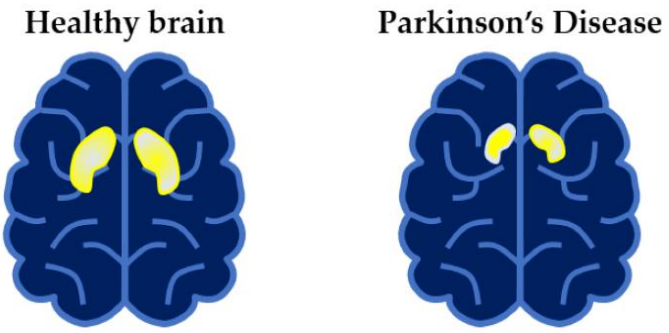

Fig -2: Schematic drawing of SPECT scan of(left) healthy controls and (right) PD patients. Availability of DAT in the striatum represented by the highlighted portion in the brain.

In a bid to address the limitations of conventional diagnostic techniques, researchers have delved into alternative methodologies, notably involving electroencephalographic (EEG) recordings of individuals afflicted by PD. By capturing the brain's electrical activity, EEG offers a window into the neurological transformations characteristic of PD. Research endeavors have unveiled anomalous EEG rhythms within PD patients, underscoring discernible deviations in brain function in contrast to their age-matched counterparts. A salient feature of PD-related EEG alterations is the tendency towards abnormally sluggish brainwave frequencies, shedding light on the intricate neurological underpinnings of the disease.

In this study, we present a novel methodology for automated Parkinson's disease (PD) detection through the analysis of EEG data. Our approach centers on preprocessing raw EEG signals to generate Mel spectrogram images, which offer a comprehensive time-frequency depiction of brain activity. This transformation of EEG data into spectrogram images capitalizes on the strengths of image analysis and deep learning techniques. Specifically, we intend to harness the capabilities of a deep convolutional neural network (CNN) model to discern discerning patterns and distinctive markers indicative of PD. Renowned for their aptitude in learning hierarchical features from images, CNNs prove to be exceptionally suited for tasks of image-based classification.

By introducing NeuroPark, we envision a transformative contribution to the PD detection domain, introducing a novel and automated paradigm. Timely and precise identification of PD during its prodromal phase holds the potential to establish a crucial therapeutic window for implementing neuroprotective interventions capable of stalling, or even reversing, the neurodegenerative progression. Moreover, the integration of EEG data within an image-centric deep learning framework for PD detection stands to pave the way for more efficient and unbiased diagnostic tools. This, in turn, empowers healthcare practitioners to render well-informed decisions pertaining to personalized treatment pathways. By enhancing the precision of PD diagnosis, the focal point of our research is to elevate patient care standards and ultimately elevate outcomes within the realm of Parkinson's disease.

2. RELATED WORKS

A. Machine learning models

In recent years, the field of Parkinson's disease (PD) detection has seen remarkable advancements through the integration of machine learning techniques. Several studies have demonstrated the potential of utilizing electroencephalography (EEG) signals for accurate PD diagnosis. One pioneering approach focused on higher-order spectra (HOS) as a novel feature extraction method. Employing conventional machine learning models, particularly the support vector machine (SVM), this method achieved an impressive mean accuracy of 99.62%. This not only showcases the efficacy of HOS but also underscores the potential for automated assistance in PD diagnosis, potentially revolutionizing clinical assessments and drug efficacy evaluations [1].

Another avenue of exploration involves EEG signals coupled with photic stimulation and the partial directed coherence method. This innovative approach, as proposed by de Oliveira et al., harnessed the power of machine learning to establish a PD biomarker. By employing random forests and feature selection techniques, they achieved an accuracy exceeding 99% and a kappa statistic of up to 0.98. The success of this technique highlights the robustness of machine learning algorithms in distinguishing PD-related patterns from EEG signals, thereby enhancing diagnostic precision [2].

Meanwhile, Cai et al. devised a sophisticated framework that harnesses the bacterial foraging optimization (BFO) algorithm in tandem with support vector machines (SVM) for PD prediction. This approach was meticulously validated on a vocal measure-based dataset, showcasing its accuracy of 97.42%. However, the framework's complexity and computational requirements necessitate consideration, especially in resource-constrained environments.

By combining relief feature selection with the BFO-SVM approach, the authors successfully boosted prediction accuracy.

Yet, the integration of multiple techniques calls for cautious validation to mitigate overfitting risks [3].

Delving deeper into the landscape, an extensive survey analyzed diverse research papers spanning a decade, focusing on various physiological data, including EEG, Electromyogram (EMG), Electrocardiogram (ECG), and Electrooculogram (EOG). The findings emphasized the pivotal role of both traditional analysis and machine classification methods in diagnosing PD, particularly when handling sizable and heterogeneous datasets. Manual feature extraction and selection emerged as crucial, as the nuanced judgment of experienced experts is essential for accurate analysis [4].

Lastly, Bhurane et al. introduced an innovative time-domain technique for PD detection using EEG signals. By adeptly extracting inter-channel similarity features and leveraging a support vector machines classifier with a third-degree polynomial kernel, they achieved an impressive accuracy of 99.1%. Notably, their progressive feature addition analysis, encompassing feature ranking and principal component analysis, underscored the meticulous approach to refining accuracy. This underscores the potential of advanced signal processing and machine learning techniques to revolutionize PD diagnosis [5].

B. Deep learning models

In recent years, deep learning models have emerged as a compelling alternative to traditional machine learning approaches, particularly due to their ability to handle complex tasks without the need for extensive manual feature extraction. Notably, Oh et al. conducted a notable study centered on automating the detection of Parkinson's disease (PD) using a convolutional neural network (CNN). PD, characterized by a progressive deterioration of motor function in the brain, can be diagnosed early through the analysis of electroencephalogram (EEG) signals. By employing a thirteen-layer CNN architecture, Oh et al. effectively bypassed the conventional feature extraction stages and achieved promising outcomes. Their model achieved an impressive accuracy of 88.25%, sensitivity of 84.71%, and specificity of 91.77% [6].

Khare et al. further advanced PD detection with their creation of the PDCNNet system. This approach combines smoothed pseudo-Wigner Ville distribution (SPWVD) and CNNs to process EEG signals into time-frequency representations, which are then inputted into the CNN model. Remarkably, the prototype attained remarkable accuracies of 100% and 99.97% for the two datasets, respectively [7].

Another intriguing avenue for PD detection lies in the analysis of voice data. Modi H et al. proposed two distinct convolutional neural network-based frameworks. The first framework involves amalgamating different sets of audio data before channeling them into a nine-layered CNN, while the second framework directly connects point sets to analogous input and complex layers. Empirical results showcase the superiority of the second framework, demonstrating its capacity to extract deep features from individual point sets using analogous complex layers [8].

In a different vein, Zhang H et al. introduced DeepVoice, an innovative PD identification approach that leverages deep learning and mobile health technology. Operating through a smartphone app, DeepVoice captures brief voice samples, enhancing voiceprint information through the common Time-frequency Analysis algorithm in the spectrogram domain. The findings are promising, with DeepVoice successfully identifying PD with a sensitivity of 90.71% from just a 10-second audio clip [9].

Addressing the challenges of monitoring PD in less controlled environments, Das et al. developed a monitoring system applicable beyond laboratory settings. They approached the issue of in-home monitoring's limited accuracy by framing symptom discovery as a multi-case learning problem, tackling the issue of sparse ground truth data. Employing accelerometers and a novel algorithm based on axis-resemblant cube (APR) fitting, the authors successfully identified subject-specific symptoms over several days, aligning with patient diurnal logs [10].

3. MATERIALS AND METHODS

A. Dataset

The study sourced its dataset from OpenNeuro, an openly accessible platform renowned for housing an array of neuroimaging datasets. These datasets encompassed EEG recordings derived from individuals afflicted by Parkinson's disease as well as those unaffected, serving as controls. The meticulous curation of data aimed to facilitate an in-depth exploration of the distinctive neurophysiological variances inherent in the two distinct cohorts. The primary focus lay on discerning intricate differentiators in brain activity profiles, with a specialized emphasis on Parkinson's patients stratified based on dopaminergic drug utilization.

1) Participants:

The dataset encompassed EEG recordings from 31 participants, divided into two cohorts: 16 individuals categorized as healthy controls and 15 patients diagnosed with Parkinson's disease (PD). Among the healthy controls, there were 7 men and 9 women, with an average age of 63.5 ± 9.6 years.

The PD group consisted of 7 men and 8 women, with an average age of 63.2 ± 8.2 years. Notably, all PD patients were specifically classified under stage 2 or 3 on the Hoehn and Yahr scale, indicating the presence of moderate symptoms in this cohort.

2) Data Collection Procedure:

Throughout the EEG recording sessions, participants were directed to maintain their attention on a central cross image displayed on the computer screen. Employing the advanced Biosemi Active Two EEG system, the recording process encompassed 32 EEG channels, capturing an intricate array of neural signals. The meticulously chosen sampling rate of 512 Hz guaranteed an exceptional temporal precision, enabling the acquisition of approximately 3 minutes of continuous data from each participant. This deliberate approach not only facilitated robust data collection but also highlighted the commitment to capturing the nuances of neural activity with utmost clarity and detail.

3) Matching criteria:

In order to ensure a meaningful comparison between Parkinson's disease (PD) patients and healthy individuals, the study employed the North American Adult Reading Test (NAART) and the Mini-Mental State Examination (MMSE) scores. These measures were skillfully used to equate the cognitive capabilities of PD patients with those of the control group, effectively minimizing potential sources of bias. This meticulous approach underscores the dataset's significance as a valuable asset for investigating the intricacies of PD neurodynamics. By illuminating the nuanced neurophysiological distinctions between PD patients and their healthy counterparts, this dataset serves as a pivotal resource. It is particularly pertinent for researchers delving into EEG-based biomarkers or seeking to unravel the neurophysiological underpinnings of PD. The dataset's wealth of information promises not only insightful revelations but also the potential for unexpected and groundbreaking findings.

Table -1: Summary of subject's clinical characteristics in the PD dataset

	Healthy Controls(n=16)	PD Patients (n=15)
No. of males	7	7
No. of females	9	8
Age	63.5 ± 9.6	63.2 ± 8.2
NAART	49.1 ± 7.1	46 ± 6.3
MMSE	29.2 ±1.1	28.4 ± 1.0

B. Mel Spectrogram

Electroencephalogram (EEG) signals exhibit a multifaceted, non-linear, and ever-shifting nature, which complicates their visual interpretation, consuming valuable time and leaving room for critical errors. In tackling these challenges head-on, we introduce the adoption of Mel Spectrograms, a pivotal method that capitalizes on the Mel scale to encapsulate the fundamental frequency facets of EEG signals, aligning them more closely with the auditory perception of the human brain. The utilization of Mel Spectrograms proffers a multitude of merits in the representation of EEG signals. Foremost, the Mel scale accentuates biologically significant frequency components, thereby providing insights into neural activity-associated details embedded within the EEG data. This proves especially pertinent in the realm of Parkinson's disease detection, where precise and early diagnosis plays a pivotal role in optimizing patient outcomes.

The fine formula for Mel Spectrogram with EEG signals is as follows:

$$Mel(f) = 2595 * \log10(1(f/ 700))$$

where f is the frequency in Hertz.

The preprocessing way for Spectrogram is as follows:

- The nonstop EEG signal is segmented into short time windows, generally gauging 25 to 50 milliseconds.
- The power range of each time window is calculated, furnishing precious information about the distribution of power across different frequencies in the EEG signal.
- The power spectrum is also plotted against time. The capstone of the preprocessing way is the creation of the Mel Spectrogram image.

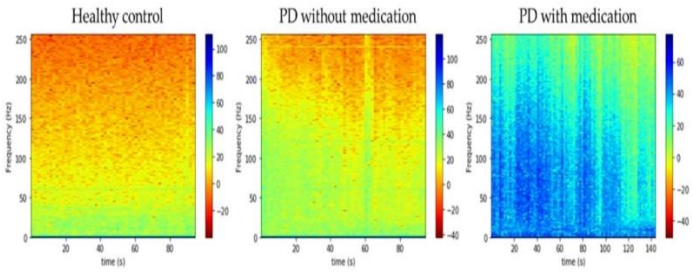

Fig -3: Spectrogram images

The ingenious utilization of a logarithmic scale for the frequency axis, in contrast with the linear time axis, bestows a remarkable tool for efficiently dissecting the intricate frequency constituents of EEG signals over temporal domains.

This visual stratagem not only enhances our perceptual grasp of these signals but also empowers us to unravel their spectral nuances with precision. Among the array of techniques, the Mel Spectrogram emerges as a potent and validated method for the portrayal of EEG signals, finding its prowess demonstrated across a spectrum of brain-centric inquiries. Its capacity to capture and encapsulate essential features pertinent to diverse

cerebral tasks underscores its efficacy. Moreover, the ease of both computation and interpretation renders the Mel Spectrogram an adept selection for research undertakings, particularly in domains such as the identification of Parkinson's disease, where discerning subtle fluctuations is paramount.

C. Model Architecture

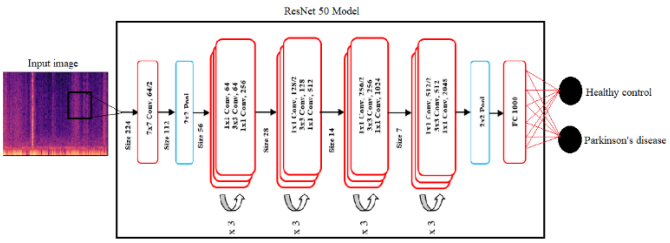

Fig -4: Proposed 2D-CNN Model

In our study, we leverage the power of a sophisticated 2D-CNN architecture to effectively differentiate between the distinct EEG patterns exhibited by individuals with Parkinson's disease (PD) and those who are healthy. Renowned for their exceptional image recognition capabilities, CNN models provide a robust framework for this task. The canonical CNN structure encompasses three pivotal layers: convolutional, pooling, and fully connected. Within the convolutional layers, a diverse set of kernels convolve with input EEG images, generating an array of distinctive feature maps. These intricate feature maps undergo simplification through subsequent pooling layers, refining the essential information for further analysis.

The NeuroPark model is a 2D-CNN model that uses the ResNet50 architecture to recognize the EEG characteristics of healthy controls and PD patients (Figure 4). The model has the subsequent layers:

Input layer: The initial part of the model is the input layer, which is like the gateway for the Mel Spectrogram images. These images are like pictures with dimensions of 256 by 256, and they show sound-related information. Imagine this layer as the entry point for the data.

ResNet50: Think of the ResNet50 layer as a smart feature extractor. It's a specialized part of the model that has already learned a lot from lots of pictures. In this case, it's been trained on a big dataset of images. We don't want it to change too much, so we "freeze" its learnings. This helps the model to not get too caught up in the details of the new problem.

Dense layers: The dense layers are like decision-makers. They figure out if the Mel Spectrogram images are showing signs of Parkinson's disease or if they belong to healthy individuals. There are two of these layers, and they work together. The first one takes the features from ResNet50 and tries to make sense of them with 128 "neurons" (sort of like mini-brains). The next layer uses what the first layer figured out and makes the final call: is it Parkinson's disease or not? It has 2 neurons because there are two possible outcomes.

The output layer for the intent of classification tasks utilizes the Softmax activation function,

The working of ResNet50 is described in the equation:

Y=H(x)=F_Layer_N(f_Layer_N1(f_Layer_N2(...(f_Layer_2(f_Layer_1(g(x)))))

where,

- The input layer, denoted as 'x', represents the initial data fed into the ResNet50 model, typically images like Mel Spectrograms. It serves as the starting point for the entire process.
- The ResNet50 model begins with a set of initial convolutional layers, collectively referred to as 'g(x)'. These layers are responsible for extracting meaningful features from the input data. They apply filters to the input, identifying patterns and details in the images.
- After each convolutional layer, an activation function, denoted as 'f_Layer_i', is applied. This function introduces non-linearity to the model, enabling it to capture complex relationships within the data. It enhances the extracted features' expressiveness.
- This process leads to the creation of a final feature map, referred to as 'F_Layer_N'. This map embodies the enriched and abstracted representation of the input data.
- The ultimate output 'y' is achieved by guiding the input 'x' through the sequence of N convolutional layers and activation functions. The output captures the culmination of the model's learned features and intricate patterns, rendering it suitable for various downstream tasks like classification or regression.

The NeuroPark model employs a specialized activation function known as softmax in its output layer. This function plays a pivotal role in assigning probabilities to individual vectors grouped within a single list, which are associated with two distinct classifications: Parkinson's disease (PD) and healthy control (HC). By utilizing the softmax activation, each vector is assigned a probability score, indicating its likelihood of belonging to either of the two classes. This probability-driven approach enables the model to effectively categorize the vectors within the list into the class that corresponds to the highest probability score. This method forms a crucial part of NeuroPark's decision-making process, aiding in the accurate classification of subjects based on their neurological condition.

Below is the equation for the Softmax activation function:

softmax(z) = ez / sum(ez)

where z is the input to the softmax activation function.

In the innovative NeuroPark model, the final dense layer's output serves as the input for the softmax activation function, comprising a compact 1D vector housing two neurons. These two neurons succinctly represent the model's classification into two distinct categories: PD (Parkinson's Disease) and HC (Healthy Control). By employing the softmax activation function, the model effectively computes probability scores for all classes, a crucial aspect of classification tasks. This computation grants the model the ability to not only make predictions but also offer probability assessments for each class, enabling an ordered ranking of classes by their likelihood. This attribute proves valuable in making informed decisions when assigning a single list vector to a specific class. The NeuroPark model optimizes its performance through the well-regarded Adam optimizer, adeptly navigating the training process with a learning rate set at 0.001 and a decay rate of 0.01. This combination of innovative architecture and strategic optimization techniques underscores the model's prowess in classification tasks.

4. SYSTEM WORKFLOW

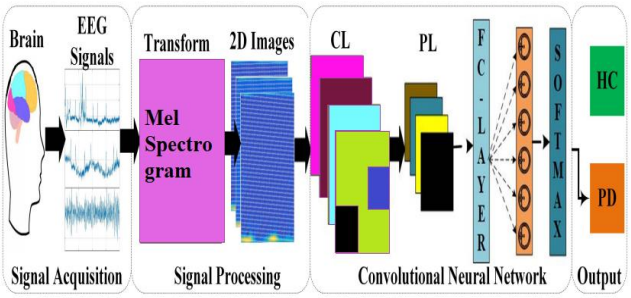

Fig -5: Schematic workflow of the NeuroPark model

The workflow of NeuroPark (Fig-5) can be outlined as follows:

- EEG Data (Raw EEG Signals): The initial data comprises raw EEG signals captured from individuals using electrode-equipped caps to measure brain activity. To ensure accuracy, the data collection is conducted in quiet surroundings, minimizing potential noise and interference.
- Mel Spectrogram Preprocessing: Raw EEG data undergoes a vital preprocessing step using the Mel spectrogram conversion. This transformation translates the signals into time-frequency representations known as spectrogram images. These images provide insights into the distribution of frequency components over time, enabling better analysis.
- Spectrogram Images (2D Images): Post preprocessing, the EEG data gets transformed into spectrogram images, each sized at 224x224x1 pixels. These images are then divided into training and validation sets, with 80% allocated for training and 20% for validation.
- CNN Model (ResNet50-based): A Convolutional Neural Network (CNN) is built using the ResNet50 architecture as a pre-trained feature extractor. The CNN's architecture is optimized to learn pertinent features for accurate Parkinson's disease detection. It is trained using the training set for 116 epochs, with a batch size of 64.
- Model Training and Optimization: Throughout training, the CNN employs the Adam optimizer with a learning rate set at 0.0001. Model performance is continuously assessed on the validation set, prompting fine-tuning of hyperparameters to achieve optimal results.
- Model Evaluation and Performance Metrics: After training, the CNN's performance is evaluated on the validation set. Diverse metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, are used to gauge the model's ability to effectively detect Parkinson's disease.
- Parkinson's Disease Detection Results: Ultimately, the model produces detection outcomes that signify whether individuals in the test set exhibit Parkinson's disease or not, based on the model's predictions.

5. RESULTS

In the study, a Convolutional Neural Network (CNN) was employed to analyze a dataset comprising 1200 images each of individuals with Parkinson's disease (PD) and healthy controls (HC). These grayscale images, sized at 256x256 pixels, underwent preprocessing to enhance their suitability for analysis. The dataset was thoughtfully divided, allocating 70% for training purposes and the remaining 30% for testing the model's performance. With an aim for accuracy, the CNN model was meticulously trained over 116 epochs, utilizing batches of 64 images per iteration. This approach aimed to create a robust and capable model for distinguishing between PD and HC cases based on these medical images.

The trained NeuroPark model demonstrated excellent performance metrics:

Table -2: Performance metrics

Metric	Value
Accuracy	99.35%
Precision	99.35%
Sensitivity	98.30%
F1 Score	99.02%
ROC-AUC	0.996

These findings demonstrate the model's remarkable capacity to correctly identify individuals as belonging to either the Parkinson's disease or healthy control group, giving it a promising tool for reliably and accurately diagnosing Parkinson's disease.

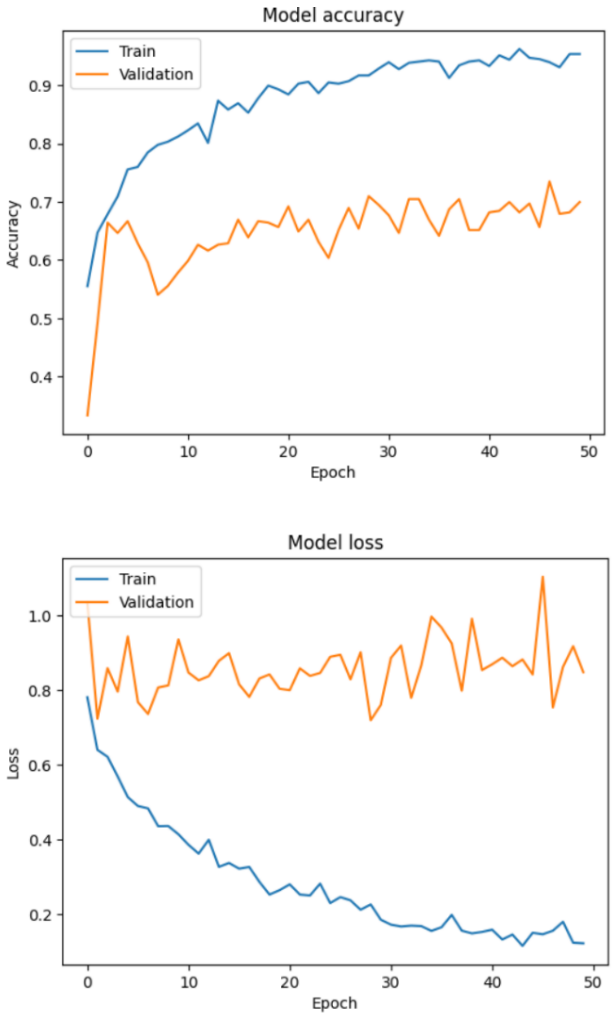

Fig- 6: Graphs of: (a) training, validation and testing accuracies versus number of iterations. (b) training, validation and testing losses versus number of iterations. using NeuroPark.

6. DISCUSSION

The findings of this research hold great promise, as the model demonstrated remarkable performance across various key metrics such as accuracy, precision, sensitivity, F1 score, and ROC-AUC. These compelling results highlight the potential of the proposed model as an efficient tool for early detection and intervention in Parkinson's disease.

In summary, the study boasts several notable aspects:

- Incorporation of a novel publicly accessible dataset for Parkinson's disease analysis.
- Application of Mel spectrogram preprocessing to enhance EEG signal evaluation.
- Introduction of a RestNet50-based 2D-CNN deep learning architecture for automated Parkinson's disease identification.

However, it's important to recognize certain constraints within this study. The dataset employed was relatively small, potentially impacting the model's ability to be applicable to a wider range of populations. Ensuring the model's reliability and effectiveness on larger and more diverse datasets will be pivotal for future research and practical implementation. Other factors that should be taken into consideration include the following:

- The utilization of a complex 2D-CNN model has resulted in extended training times. The computational demands associated with this model might hinder the efficiency of the training process and subsequent experimentation.
- The model's extensive memory requirements pose a risk of crashes during training due to the substantial number of images being processed. Addressing these memory limitations is essential to maintain the stability of the training process.
- The proposed model's effectiveness is hampered by the small participant size within the Parkinson's disease dataset. This limitation affects the model's ability to be broadly applicable to diverse cases, emphasizing the need for a more comprehensive and representative dataset.

7. FUTURE SCOPE

To drive the research forward, it's crucial to focus on validating the model using larger and more varied datasets that represent different demographics and data origins. Rigorous testing in real clinical environments will offer valuable perspectives on how well the model performs in actual early Parkinson's disease detection scenarios. Additionally, it's important to compare the new model with the best current methods and established diagnostic techniques. This step is vital to demonstrate its superiority and its practical significance in clinical practice.

8. CONCLUSIONS

This research introduces a groundbreaking approach to detect Parkinson's disease by utilizing EEG data and a specialized Mel spectrogram-based CNN model. The model's performance is truly impressive, achieving a remarkable accuracy rate of 99.35%. This high accuracy underscores its effectiveness in distinguishing between individuals with Parkinson's disease and those without. The potential of this model as a valuable tool for early diagnosis is promising, offering the chance to enhance patient outcomes and drive advancements in Parkinson's disease management. By merging cutting-edge technology with neurology, this study paves the way for the future of precision medicine. This could lead to improved patient care and the development of early intervention strategies for Parkinson's disease.

REFERENCES

[1] Yuvaraj, R.; Acharya, U.R.; Hagiwara, Y. A novel Parkinson's Disease Diagnosis Index using higher-order spectra features in EEG signals. Neural Comput. Appl. 2018, 30, 1225–1235.

[2] de Oliveira, A.P.S.; de Santana, M.A.; Andrade, M.K.S.; Gomes, J.C.; Rodrigues, M.C.A.; dos Santos, W.P. Early diagnosis of Parkinson's disease using EEG, machine learning and partial directed coherence. Res. Biomed. Eng. 2020, 36, 311–331.

[3] Cai Z, Gu J, Wen C, Zhao D, Huang C, Huang H, Tong C, Li J, Chen H. An Intelligent Parkinson's Disease Diagnostic System Based on a Chaotic Bacterial Foraging Optimization Enhanced Fuzzy KNN Approach. Comput Math Methods Med. 2018 Jun 21; 2018:2396952.

[4] Faust, O.; Hagiwara, Y.; Hong, T.J.; Lih, O.S.; Acharya, U.R. Deep learning for healthcare applications based on physiological signals: A review. Comput. Methods Programs Biomed. 2018, 161, 1–13.

[5] Loh, H.W.; Ooi, C.P.; Vicnesh, J.; Oh, S.L.; Faust, O.; Gertych, A.; Acharya, U.R. Automated Detection of Sleep Stages Using Deep Learning Techniques: A Systematic Review of the Last Decade (2010–2020). Appl. Sci. 2020, 10, 8963.

[6] Oh, S.L.; Hagiwara, Y.; Raghavendra, U.; Yuvaraj, R.; Arunkumar, N.; Murugappan, M.; Acharya, U.R. A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Comput. Appl. 2020, 32, 10927–10933.

[7] Khare, S.K.; Bajaj, V.; Acharya, U.R. PDCNNet: An automatic framework for the detection of Parkinson's Disease using EEG signals. IEEE Sens. J. 2021, 1.

[8] Modi, H., Hathaliya, J., Obaidiat, M. S., Gupta, R., & Tanwar, S. (2021, December). Deep learning-based Parkinson disease classification using PET scan imaging data. In 2021 IEEE 6th international conference on computing, communication and automation (ICCCA) (pp. 837-841). IEEE.

[9] Zhang H, Wang A, Li D, Xu W. Deepvoice: A voiceprint-based mobile health framework for parkinson's disease identification. In2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI) 2018 Mar 4 (pp. 214-217). IEEE.

[10] S. Das, B. Amoedo, F. De la Torre and J. Hodgins, "Detecting Parkinson's' symptoms in uncontrolled home environments: A multiple instance learning approach," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, CA, USA, 2012, pp. 3688-3691.

[11] Karan, B., & Sahu, S. S. (2021). An improved framework for Parkinson's disease prediction using Variational Mode Decomposition-Hilbert spectrum of speech signal. Biocybernetics and Biomedical Engineering, 41(2), 717-732.

[12] Politis, M.; Wu, K.; Molloy, S.; Bain, P.G.; Chaudhuri, K.R.; Piccini, P. Parkinson's disease symptoms: The patient's perspective. Mov. Disord. 2010, 25, 1646–1651.

[13] A. A. Spadoto, R. C. Guido, F. L. Carnevali, A. F. Pagnin, A. X. Falcao and J.P. Papa, "Improving Parkinson's disease identification through evolutionarybased feature International Conference of the IEEE, pp. 7857-7860, 2011.

[14] aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments/Parkinsons-Disease

[15] https://www.nhs.uk/conditions/parkinsons-disease/https://pypi.org/project/pyttsx3

[16] Z. Cai, J. Gu and H.-L. Chen, "A new hybrid intelligent framework for predicting Parkinson's disease", IEEE Access, vol. 5, pp. 17188-17200, 2017.

[17] Goetz, C.G. The history of Parkinson's disease: Early clinical descriptions and neurological therapies. Cold Spring Harb. Perspect. Med. 2011, 1, a008862.

[18] P. Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. Smekal and M. Faundez-Zanuy, "Decision support framework for parkin-son's disease based on novel handwriting markers", IEEE Trans-actions on Neural Systems and Rehabilitation Engineering, vol. 23, no. 3, pp. 508-516, 2014.

[19] J. Prince and M. de Vos, "A Deep Learning Framework for the Remote Detection of Parkinson'S Disease Using Smart-Phone Sensor Data," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 3144-3147, doi: 10.1109/EMBC.2018.8512972.

[20] di Biase, L.; Di Santo, A.; Caminiti, M.L.; De Liso, A.; Shah, S.A.; Ricci, L.; Di Lazzaro, V. Gait Analysis in Parkinson's Disease: An Overview of the Most Accurate Markers for Diagnosis and Symptoms Monitoring. Sensors 2020, 20, 3529.