TPM Vol. 32, No. 4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

AI-DRIVEN INSIGHTS: PREDICTING COGNITIVE DECLINE AND ENHANCING MOTOR FUNCTION RECOVERY IN PARKINSON'S DISEASE THROUGH NEUROIMAGING, BEHAVIORAL DATA, AND ROBOTICS

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Abstract Parkinson's disease (PD) is a neurodegenerative disorder characterized by progressive degeneration of dopaminergic neurons and clinical features of tremor, rigidity, postural instability, and bradykinesia. Early accurate diagnosis remains challenging due to interindividual variability and the inherent limitations of standard imaging modalities. We describe a new multimodal approach integrating neuroimaging, behavioral data analysis, robotics and artificial intelligence. MRI scans were pre-processed and processed using deep learning models—InceptionV3, VGG19, and GANs—to obtain features. The behavioral data was represented using recurrent neural networks (RNNs), while the real-time monitoring of the patient was guaranteed using a robotic-assisted system. The dataset employed is the Parkinson's Progression Markers Initiative (PPMI) and UPDRS-based behavioral recordings. Accuracy, precision, recall, and F1-score metrics were used to compare performance. Overall, AI model achieved 99.5% accuracy in PD classification. CNN-based neuroimaging and RNN-based behavioral data integration improved motor and cognitive decline predictions. Explainable AI revealed salient neuroanatomical features accountable for the model's choices. Robustness was guaranteed by internal cross-validation as well as external validation using independent datasets. This multimodal AI-based approach enhances diagnostic accuracy significantly and facilitates personalized rehabilitation therapy for PD. It has a high potential to bridge the gap between clinical trials and real-world application, paving the way for future developments in neurodegenerative disease management.

Keywords MRI, CT, PET, InceptionV3, VGG19, CNN, RNN, GAN

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder that primarily affects the basal ganglia, a brain region responsible for regulating movement. However, its pathology extends beyond motor impairments, involving widespread dopaminergic and non-dopaminergic pathways that manifest as diverse nonmotor symptoms (NMS).

The growing prevalence of PD due to the aging population is emerging as a major challenge for healthcare systems worldwide [1]. Conventional PD management relies heavily on subjective evaluations of clinical symptoms, which often fall short in addressing the disease's highly heterogeneous nature and complex progression [2].

The WHO and Global Burden of Disease Study have identified Parkinson's disease as one of the fastest-growing neurological disorders worldwide. Between 1990 and 2016, the number of people with PD more than doubled, from 2.5 million to over 6 million, while figures suggest that by 2040 this number will increase to 12 million [3]. Aging populations and increased longevity, particularly in low- and middle-income countries, are responsible for this increase, thus posing an ever-greater burden on health systems [4].

Among the nonmotor symptoms, cognitive problems—which can range from mild cognitive impairment to dementia—are common and often impactful. These symptoms present themselves at various stages during the disease course. The cognitive decline in PD (PD-CD) has recently been recognized as a pivotal characteristic of

PD progression, instigating a great deal of research into designing predictive models that can efficiently forecast and manage PD-CD [1–2].

Cognitive impairment and its relationship with age, visual hallucinations, postural instability, gait disorders (PIGD), and olfactory dysfunction have been well documented. Biomarkers such as CSF tau, levodopa responses, and imaging modalities such as dopamine active transporter (DAT) SPECT have emerged as strong predictors. Studies have shown that low DAT availability in regions like the putamen and caudate correlates with cognitive decline [4–7].

Advances in artificial intelligence (AI) offer new avenues to deepen our understanding, improve prediction, and develop better treatment strategies for PD. Novel AI-driven diagnostic and therapeutic tools have the potential to revolutionize PD care and address the limitations of current symptom-based evaluations, ultimately helping to meet rising global healthcare demands [3].

Over the past decade, numerous studies have attempted to predict PD-CD using clinical assessments, biomarkers, and neuroimaging techniques. These predictors offer valuable prognostic insights for disease management, the design of clinical trials, and therapeutic decision-making.

Two of the most commonly used tests for cognitive assessment in PD are the Montreal Cognitive Assessment (MoCA) and the Movement Disorder Society Unified Parkinson's Disease Rating Scale Part I (MDS-UPDRS-I). MoCA, originally created to detect mild cognitive impairment in Alzheimer's disease, evaluates memory, executive function, and verbal fluency. In contrast, MDS-UPDRS-I measures more generally non-motor symptoms like cognitive impairment, mood disturbances, and psychosis. Higher scores on these measures reflect greater risk for PD-CD [8–11].

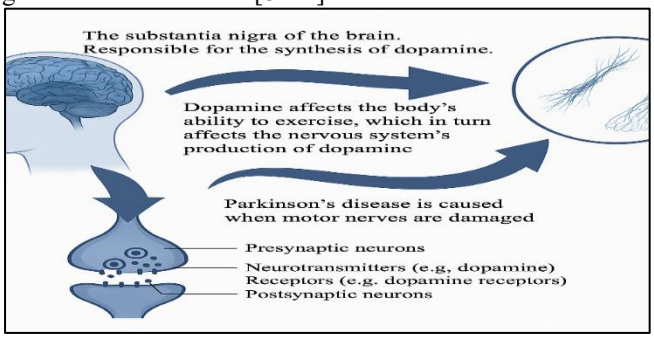

Fig.1. The relationship between the brain and the parts of the body (adopted from [25])

Traditionally, classical statistical models have been used to predict PD-CD. However, machine learning (ML) approaches are revolutionizing the field by allowing scientists and doctors to take in larger and more complex datasets, including neuroimaging and clinical data, and provide greater accuracy of predictions. ML models show efficiency in pattern identification in multi-dimensional data. They could outperform traditional methods in predicting cognitive outcomes in PD [12]. AI-driven solutions built on the back of machine learning algorithms and neural networks have shown unparalleled success in handling immense amounts of complex data. Neuroimaging techniques like MRI or PET scans provide insight into structural and functional brain changes associated with Parkinson's disease, while behavioral data further capture nuanced motor and non-motor symptoms. In addition, robotics, backed by AI, allows for personalized rehabilitation approaches designed to improve motor recovery [13-14]. This way, AI models, by combining neuroimaging inputs, behavioral metrics, and robotics, can find the same expression of patterns indicating cognitive decline and motor malfunction in people suffering from PD with a unique accuracy [15]. In this study, we adopt an AI-driven methodology to predict PD-CD using neuroimaging data (DAT SPECT). We evaluate the prognostic accuracy of MoCA and MDS-UPDRS-I in forecasting cognitive decline over different time horizons. By employing machine learning, we aim to provide more accurate and personalized predictions and contribute to more effective diagnostic and therapeutic approaches towards PD-CD.

This new framework integrates neuroimaging data, behavioral data, and robotic interventions to predict cognitive decline while informing interventions that promote motor recovery and improve overall patient outcomes. This proposed proof of concept is relevant to interdisciplinary interventions that come from the use of neuroimaging, analysis of behavioral data, and robotic interventions in any provided AIs for predicting cognitive decline while improving motor recovery for Parkinson's disease. These integrated interdisciplinary tools seek to close the gap between clinical diagnostics and a personalized treatment, which is key to improving outcomes and quality of life for patients. This interconnective methodology adds weight to current evidence, making the case that AI will revolutionize the management of neurodegenerative disorders [16-17].

II. LITERATURE REVIEW

PD is a neurodegenerative disorder with multifactorial etiology, which complicates early diagnosis and management due to its effect on both motor and cognitive functions. Cognitive decline is a particularly formidable challenge because of its gradual and complex nature. Recently, AI, especially ML and DL techniques, has been emerging as a promising approach in enhancing biomarker detection associated with PD. Neuroimaging techniques like MRI, CT, and PET, combined with CNN, have been used to detect structural and functional changes in the brain associated with the disease, with predictive accuracies higher than 85%. Behavioral data,

such as gait analysis, metrics of tremor, and speech impairments, have also been studied as potential non-invasive diagnostic measures that can, in turn, provide real-time feedback regarding disease progression. AI integrated with robotic-assisted therapies and speech analysis has given further impetus to personalized disease monitoring and rehabilitation, bringing forth its clinical potential. But challenges such as data heterogeneity, model generalization, and ethical considerations concerning patient privacy are standing in the way of its clinical integration. This literature review covers the role of AI-driven neuroimaging, speech analysis, and behavioral metrics in the detection and prediction of Parkinson's Disease, discussing recent progress, challenges that remain, and future directions toward the improvement of early diagnosis and intervention strategies.

Combined with brain structural connectivity from diffusion MRI, convolutional neural networks (CNNs) have been looked into by Chen et al. (2021), in using them to detect incident mild cognitive impairment (MCI). Their architecture achieved an accuracy of 85.7%, which is in direct correlation with the effectiveness of CNNs in identifying early brain changes linked to cognitive decline. The research suggests the capabilities of deep learning combined with neuroimaging for future possibilities in early and non-invasive screening of neurodegenerative conditions.[18]. Additionally, NLP-based predictive models have examined speech and language patterns for the same purpose, thus providing a non-invasive, inexpensive method for longitudinal monitoring of cognitive impairment. As underlined by [19], this points to the potential of AI in improving early diagnosis and intervention strategies.

Behavioral data, such as gait analysis, tremor metrics, and handwriting patterns, provide vital insights into PD symptoms. AI frameworks leveraging these metrics have demonstrated efficacy in tracking disease progression. For example, wearable sensors integrated with RNNs have distinguished PD patients from healthy controls with accuracy of more than 90% [20]. Furthermore, multimodal AI models analyzing electronic health records (EHRs) and patient-reported outcomes have facilitated personalized disease progression models. These tools enable early interventions, potentially mitigating motor and cognitive symptoms.

Robotic-assisted therapy has become one of the transformative tools for rehabilitation concerning PD. AI-powered exoskeletons and robotic devices offer customized motor training by automatically adapting to the needs of a patient. Reinforcement learning algorithms integrated into such systems further optimize therapy through continuous modifications in resistance and support levels based on feedback in real time [21]. Furthermore, this integration of robotic interventions with virtual reality environments creates an immersive environment for training, which helps enhance patient engagement and motor recovery [22].

MRI techniques have been a key factor in the development of knowledge about PD. Variants of deep learning, such as 2D and 3D CNNs, have successfully extracted biomarkers from MRI images. For instance, authors used data from the PPMI and followed a series of preprocessing steps involving bias field correction and Z-score normalization to train CNN models[23]. The 3D CNN model yielded higher classification accuracy at 88.9%, as opposed to 72.22% for the 2D model.

Recent surveys, such as those by [23], emphasize the potential of ML techniques in uncovering hidden patterns in high-dimensional neuroimaging data despite challenges in translating such methods into clinical practice. Future research needs to be done at disease-specific, task-specific, and technology-specific levels to enable safe clinical integration.

Speech impairments are among the earliest signs of PD, making speech analysis a valuable diagnostic tool. Hazan et al. (2012) demonstrated a vowel-based ANN model that achieved 91% prediction accuracy for PD, underlining the role of speech features in early detection. Similarly, [24], introduced intrinsic mode function cepstral coefficients to enhance the classification accuracy by up to 20% compared to the standard methods. Other studies have explored multi-lingual speech-based tasks in the classification of PD. The authors proposed using eGeMAPSv2 with an accuracy and AUC of 84.73% and 92.18%, respectively, representing the feasibility for automated diagnosis through a smartphone application.

Global research emphasizes how important the intersection of neuroimaging with speech analysis and behavioral metrics is in developing comprehensive diagnostic tools. [25], compared several DL models to establish CNNs as the best architecture to detect PD and neurological conditions. AI has also become more applicable in PD research with the integration of speech data from different linguistic and cultural contexts. Multinational datasets and voting-based ML approaches have further refined the accuracy and generalizability of diagnostic tools, thus demonstrating a very promising future for automated PD detection.

Parkinson's disease is a neurodegenerative disorder characterized by progressive deterioration of motor and non-motor functions. Early diagnosis of PD is considered to be of the highest priority to allow early treatment and management. Recent studies have established the potential of speech analysis in the prediction of PD since impaired vocal functions, such as changes in phonation, decreased intensity of speech, and impaired articulation, are among the most significant early signs of the disease. The authors proposed a vowel-based ANN model for PD prediction using single vowel phonation. They analyzed speech samples of 48 PD patients and 20 healthy subjects of different types, including vowels, numbers, words, and short sentences. They have shown that single-type vowel models are better than other models with 91% accuracy, 99% sensitivity, 82% specificity, and an AUC of 91%. Similarly, [26] introduced a novel intrinsic mode function cepstral coefficient (IMFCC) feature derived using empirical mode decomposition (EMD) to address challenges in speech signal processing. Their experiments on two datasets showed a significant improvement in classification accuracy—10–20% higher than conventional features like Mel-frequency cepstral coefficients (MFCC). According to the authors [27-28], extended this line of inquiry to classify individuals as healthy, PD-affected, and probably affected using a host of speech features like LPCC, MFCC, and handcrafted features. This study emphasized temporal modulation of speech features while

modeling the progression of PD. Using these features, it showed classification accuracies within a range of 80% to 90% have proposed a voting-based machine learning model for classifying PD patients in a Korean population, which addresses the need for accessible diagnostic tools that are also efficient. The proposed model utilized the eGeMAPSv2 feature set and new acoustic features, achieving 84.73% accuracy with an AUC score of 92.18%. Their work underlines the potential integration of machine learning models into mobile applications for automated PD diagnosis.

Other cross-linguistic studies, such as by [29], illustrated the effectiveness of machine learning for early PD diagnosis across languages. With data from both the USA and Germany, their classification results ranged from 75% to 85%, depending on the training-testing scenario. The study also showed that linguistic variations have a significant impact on the dominance of features, indicating the need for localized model adaptation [30-35].

These studies together point to a future of promise for speech analysis and machine learning in the pursuit of early diagnosis of PD. By leveraging novel features and robust classification techniques, researchers are getting closer to developing accessible, cost-effective, and efficient diagnostic tools that can be integrated into real-world applications. Future research should be directed at refining feature extraction techniques, cross-linguistic adaptations, and enhancing the interpretability of predictive models [36-38]. However, the application of AI in PD has its own challenges, in the forms of data heterogeneity, limited generalization of models, and patient privacy ethical issues. Future efforts should therefore be directed at establishing interpretable AI models with standardized frameworks for data sharing between institutions. Moreover, incorporation of such AI-driven techniques into standard clinical practice has to be preceded by necessary validation procedures to ensure the safety and efficacy of the method [39-40].

In the end, by employing ML and DL methodologies, major strides are taken in the analyses of neuroimaging data, behavioral metrics, and speech characteristics. These include neuroimaging applications, mainly regarding MRI and PET scans, which have determined structural and functional brain alterations in PD with high predictive accuracy[41-45]. Meanwhile, behavioral and speech-based analyses provide low-cost and noninvasive complementary strategies to the traditional ones that allow for real-time monitoring and personalized interventions. Artificial Intelligence-driven robotic systems are revolutionizing rehabilitation by providing adaptive motor training and enhancing patients' motivation. However, challenges related to model interpretability, data standardization, and clinical integration remain, which require further research [46-49]. This literature review therefore illustrates the transformative role of AI in understanding and managing PD, paving the way toward more effective, patient-centered care and robust clinical applications.

III. Problem definition

Although traditional clinical interventions in conditions as complex as PD (Parkinson Disease) cannot begin to conquer all limitations, the explosion in use of AI-enabled wearable and portable devices creates some degree of complexity and volume of data. This trend adds another layer of challenge to the task of merging these new data sources into established clinical measures. Integrating these new technologies into the established clinical framework is crucial so that the deep knowledge gained by clinicians over decades of research and patient management can serve as a unifying background. Without this integration, the data from new technologies, however promising, may have minimal, if any, clinical value. This paper presents the heart of the challenge with the integration of data produced by the novel technologies and the traditional clinical data, with emphasis on PD as demonstrated in Figure 2.

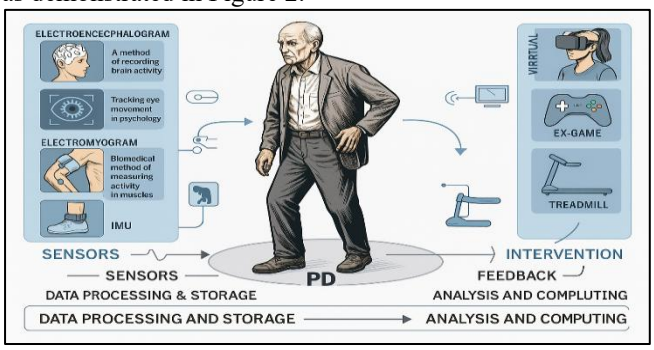

Fig.2. Wearable and intervention systems for PD, classification, and related technologies. ([25])

IV. Data Extraction

Data for this study were extracted from the LCC database, which is a comprehensive longitudinal resource built by the Michael J. Fox Foundation to accelerate research into Parkinson's Disease. The dataset encompasses various types of data that are important for disease progression understanding. It was designed to study motor and non-motor symptoms of the disease through clinical evaluations such as UPDRS, MMSE, and MoCA scales. Biospecimen samples (such as blood and CSF) were collected to identify and validate neuroimaging data were acquired (high-resolution T1- and T2-weight MRI scans and DaTscan SPECT imaging) to investigate structural changes in the brain and degeneration of dopaminergic neurons, respectively. The longitudinal design of this dataset enabled the tracking of PD progression over years, while a robust control group of healthy individuals allowed for baseline comparisons. Data was accessed from the LRRK2 Cohort Consortium (LCC) website, supporting global research efforts to enhance understanding and treatment of PD.

Data collection involved the extraction of neuroimaging data, including T1 and T2-weight MRI scans and DaTscan SPECT images, from the publicly available LCC database. The LRRK2 Cohort Consortium (LCC) website acts as a global resource, fostering international collaboration in research work on Parkinson's disease at https://www.michaeljfox.org. The database granted access to an extensive collection of imaging data and allowed researchers from all over the world to contribute to further understanding and treating Parkinson's disease. This open-access model allows assurance that the data in this study are reliable and representative of international research efforts in the field.

V. METHOD

This research proposed a hybrid artificial intelligence framework that combines neuroimaging, behavioral analysis, and robotics to increase the prediction and management of Parkinson's disease (PD), especially concerning cognitive and motor decline. The framework works with five primary stages: data acquisition, preprocessing, feature extraction, model fusion, and validation, with real-time deployment for clinical feedback and therapeutic decision-making as mentioned in Figure 3.

At the data acquisition stage, high-resolution PET and CT scans are obtained, focusing on regions of the brain such as the substantia nigra and basal ganglia in order to detect PD structural and functional defects. Concurrently with the above, longitudinal behavior data are obtained by the assessment of motor function (e.g., tremor and gait), speech, as well as cognitive tests of memory and attention. Patient demographics and clinical history like age, sex, disease duration, drug status, and UPDRS scores are also incorporated as auxiliary inputs to enrich the dataset.

Preprocessing includes noise reduction, intensity normalization, and spatial co-registration of neuroimaging data for scan registration across subjects. Class imbalance and training diversity are addressed with Generative Adversarial Networks (GANs) to create additional imaging and behavioral data. Behavioral time-series data are smoothed and resampled to a common temporal resolution, and missing values are filled in using interpolation for continuity of data.

At the feature extraction stage, an integrated Convolutional Neural Network (CNN) architecture involving VGG16 and Inception blocks is employed to derive relevant features such as cortical thickness, dopaminergic activity, and texture-based abnormality. Concurrently, behavioral features such as tremor rate and memory error rates are processed via a Bidirectional Recurrent Neural Network (RNN) coupled with a Transformer encoder to capture long-range temporal dependencies. Furthermore, latent embeddings learned from the discriminator of the GAN are also used to increase generalizability and prevent overfitting.

These multi-stream features are then aggregated in a multimodal fusion and classification module. Features from the neuroimaging and behavioral streams are concatenated inside a fusion layer and fed to a dense classification head, predicting on both presence of PD vs. control and anticipated trajectories of cognitive vs. motor decline. Categorical cross-entropy loss is utilized in training the model, and Adam optimizer is used to optimize for effective convergence.

For interpretability and model validation, internal and external data are subjected to stratified k-fold cross-validation (k=10) for testing performance. Moreover, explainable AI (XAI) tools such as Grad-CAM are utilized for visualizing the most important brain regions influencing model predictions, thus increasing clinical transparency and trustworthiness.

Finally, the system supports real-time robotics deployment and integration. The trained model interacts with robotic-assisted platforms enabling continuous, in-home patient monitoring and adjust therapeutic strategies based on AI-generated feedback. Automated data preprocessing, diagnostic report generation, and distribution of personalized therapeutic recommendations to clinicians are facilitated by a cloud-based infrastructure, supporting effortless, evidence-based PD management which is mentioned in Figure 3.

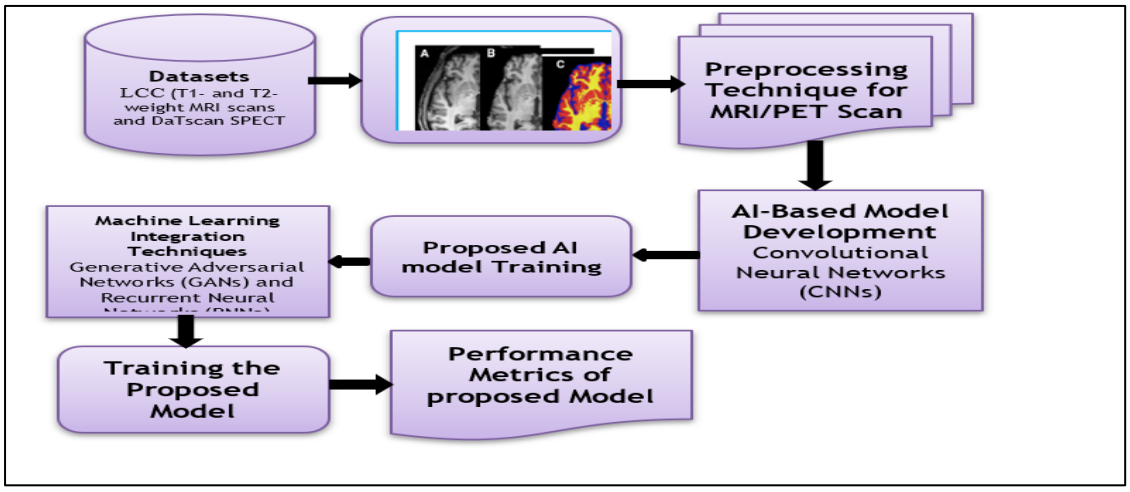

Fig.3. Proposed methodology for early detection of PD using AI model and ML approaches

VI. MRI Data Sample Distribution

In this study, LCC T1, T2-weighted, and SPECT DaTscan data are employed. Images are acquired with 1.5–3 Tesla scanner. Time of scan is around twenty to thirty minutes. T1, T2-weighted MRI images are acquired as three-dimensional sequence on axial, sagittal, and coronal locations with 1.5 mm or less thickness. The two MRI description sets are presented further for tabulated illustrations-T1 and T2 weighted and SPECT DaTscan, respectively. Two datasets are utilized now, i.e., T1- and T2-weighted SPECT DaTscan dataset. The T1, T2-weighted MRI dataset contains 50 subjects in total: 25 subjects (Male-12, Female-13) with PD diagnosis and 25 subjects (Male-12, Female-13) as HC, in total a total of 15,000 MRI images of different size. Among the 15,000 MRI images, there are 6,200 images of PD subjects and 8,800 images of HC subjects. The SPECT DaTscan dataset also consists of 45 subjects in total, where 23 subjects (Male-11, Female-12) have Parkinson's disease (PD) and 22 subjects (Male-10, Female-12) are healthy controls (HC), with a total of 25,000 MRI images. Out of these 25,000 MRI images, 7,800 images are for PD subjects and 17,200 for HC subjects.

A. Medical Treatment Plan

Treatment for Parkinson's disease depends on the severity of symptoms and neuroimaging findings; however, dopaminergic medications remain the cornerstone. Levodopa/Carbidopa replenishes dopamine, starting at 100mg/25mg three times daily and titrated to achieve symptom control, while Dopamine Agonists, such as Pramipexole, 0.125mg daily up to 1.5mg/day, stimulate dopamine receptors, especially in early-stage PD. Monoamine Oxidase-B Inhibitors, such as Rasagiline, 1mg/day, delay the breakdown of dopamine and are suitable in conditions of mild symptoms. In addition, COMT Inhibitors like Entacapone (200mg with each Levodopa/Carbidopa dose) improve efficacy in moderate deficits. Younger patients with tremor may be treated with Anticholinergics; Trihexyphenidyl, 1mg bid. Non-dopaminergic agents include Amantadine, 100mg once or bid for dyskinesias, SSRIs/SNRIs, Sertraline 25–50 mg/day for mood disorders and Clonazepam 0.5mg or Melatonin 3–5mg q HS for REM sleep behavior disorder in concert with appropriate sleep studies.

Furthermore, Treatment for Parkinson's disease is increasingly neuroimaging- and behavior-based. For those patients with severe dopaminergic neuron loss evidenced by DAT-SPECT or PET scans, higher doses of Levodopa/Carbidopa in combination with COMT inhibitors are prescribed for the optimization of motor control. On the other hand, if there is evidence of cognitive decline, as established through fMRI or behavioral testing, then dopamine agonists and anticholinergics should be avoided in order to minimize cognitive side effects. In such cases, Levodopa remains the best option to balance efficacy and safety.

B. Inclusion Criteria

Patients aged 50-80 years are included in the study. Only PD and HC subjects are included.

C. Exclusion criteria

Patients below 50 or above 80 years are excluded from the study. Other categories of subjects such as SWEDD, PRODROMAL, etc., are also excluded.

D. Image pre processing

MRI images are provided as DICOM, a standard file format used to store and distribute medical images such as X-rays, computed tomography (CT) scans, and MRIs. The DICOM format includes many image-related metadata: patient information, acquisition details of the image, and other medical information. However, it is cumbersome to work with a DICOM file format when using these images in some form of machine learning application. This is one of the reasons why DICOM images are typically converted into image formats like png or jpg for image classification: so that DICOM files can be utilized for image classification with the majority of machine learning libraries and frameworks which typically don't take DICOM files. In most cases, although Python does have libraries for reading and manipulating DICOM images, it might be easier to rescale the images to some more commonly used formats such as png or jpg and then use general image manipulation packages on the images. A second reason to translate DICOM images to jpg is that DICOM standard may utilize different pixel representations and bit depths, based on the hardware and software that was used to generate the image; however, the jpg pixel representation and bit depth have standardized, so greater consistency and ease of manipulation can be attained. Another likely reason png, jpg images don't lose any information when they're compressed, unlike certain other picture types, is that the medical imaging world is so obsessed with even a suggestion of loss of information being real. All DICOM (.dic) file format images within this research are initially converted to.jpg using the Micro DICOM Viewer desktop application. The original dimensions of the image are 256×256×3. The images which produce empty tuples have been deleted from the chosen images. Candidates for such empty tuples are those that generate null arrays for which the machine-learning models cause tons of misclassification. The threshold for those images to be removed is 30 pixels. Ten images are cropped and striped using Python library functions. Ten, images are normalized using batch normalization. The MRI images, after preprocessing, result in a size of 224×224×3 and are fed into the models as such.

E. Model Development

The hybrid VGG19 (Visual Geometry Group 19) model and two blocks of the InceptionV3 model. This architecture comprises many critical stages, including the bottom sixteen layers of VGG19 that comprise Block-1. In Block-2, it expects the output of Block-1 as input, a matrix of 7×7×512, where the input has gone through an inception-reduction block to make a 7×7×640 output matrix. Similar activity follows in Block-3 to obtain an output of 3×3×832. The last stage, Block-4, consists of global average pooling followed by a fully connected layer, and it ends with a sigmoid layer that classifies the input as either Parkinson's Disease or healthy control.

Inception-reduction blocks have been incorporated into Block-2 and Block-3. The inception block of Block-2 is constituted of four 1×1 convolutions, three 3×3 convolutions, and a max pooling with a kernel size of 3×3. (1×1) convolutions decrease the number of input channels and, therefore, accelerate the training process, whereas (3×3) convolutions capture the low-level features of an image such as edges, lines, and corners. The final design concatenates the features and passes them through a reduction block, made up of three 3×3 convolutions and one 1×1 convolution, coupled with max-pooling layers. This design brings improved efficiency to the model and decreases computational cost.

Block-3: Output from Block-2 comes as input to the inception block, which consists of four convolutions of size (1×1), three reductions of size (7×1) and (1×7) each, and an average pooling of size (3×3). Employing (7×1) and (1×7) convolutions instead of a single (7×7) convolution reduces model cost due to factoring of the operations. In Block-3, there is a reduction block composed of two 1×1 convolutions, two 3×3 convolutions, two (7×1) and (1×7) convolutions, and a layer of (3×3) max pooling. Further, the output from Block-3 will pass to Block-4 to have global average pooling of the general image features. The output of which will then be passed through the fully connected layer, eventually finalizing the classification using the sigmoid activation. In addition, the model accepts as input: (224×224×3) image with the last probability through sigmoid layer that was displayed. The rest of GANs architecture of Generative Adversarial Networks, which consist of two neural networks: the Generator and the Discriminator. The Generator Network generates synthetic data in view of the input training data to potentially resemble the distribution of real data. The Discriminator Network, which will assess the generated data, tells if it is real or fake by giving a score, 0 for fake and 1 for real. In training, these networks engage in a zero-sum game-the Generator enhances its ability in generating realistic data to potentially fool the Discriminator and vice versa. This, in an adversarial manner, iteratively improves the two networks, enabling a GAN to generate truly realistic synthetic data. in Figure 4 and Table 1.

Table.1. Proposed hybrid Model Convolution layer description

Phase	**Mapping Features**
Block-1	7×7×512
Block-2	7×7×640
Block-3	7×7×8321
Block-4	11024
Connected Layer	1024
Sigmoid	1

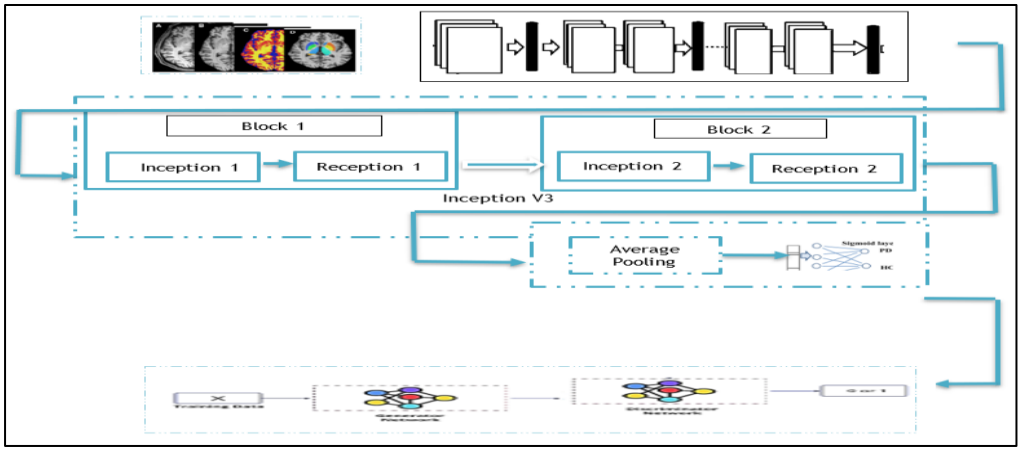

Fig. 4. Proposed Hybrid model of CNN with RNN and GANs

F. Brain imaging slices for Parkinson's Disease

The model is designed to incorporate structural MRI-based neuroimaging data in analyzing Parkinson's Disease, as shown in Figure 5. The neuroimaging processing pipeline initiates with the acquisition of high-resolution T1- weighted MRI images, which form the very basis of further analysis. This pipeline involves several steps that are quite essential for brain extraction and bias field correction in order to remove non-brain tissues and further homogenize the images. This is followed by segmentation into tissue types, as shown in Panel C, of the brain into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). Subcortical structures are then segmented into the thalamus, putamen, and globus pallidus, among others, for further processing, detailed in Panel D. For better contrast in the segmentation of subcortical structures, a T1-weight white matter nulled image is generated in Panel E, which again helps in segmenting the globus pallidus into its internal and external subregions, detailed in Panel F. FLAIR imaging (Panel G) was performed to null the signal of CSF and thereby enhance the detectability of WMHs, which are quantified and highlighted in red in Panel H. These structural abnormalities are key markers for neurodegeneration and serve as potential biomarkers for Parkinson's Disease.

G. Neuroimaging Integration for Cognitive Decline Prediction

This neuroimaging pipeline, which uses a combination of T1-weighted and FLAIR MRI images, provides a robust framework for detecting and analyzing structural changes associated with PD. By incorporating these detailed imaging processes, the model can be used to help in early diagnosis, disease progression monitoring, and the identification of neurodegenerative biomarkers. The proposed hybrid model will adopt both deep learning and sophisticated neuroimaging techniques to enhance the early detection and monitoring of PD. It will improve the prediction of cognitive and motor impairments by incorporating convolutional neural networks into structural MRI data, thus offering a strong tool for clinicians and researchers studying neurodegenerative diseases like PD.

H. Behavioral Metrics Analysis

Consequently, wearable sensors and mobile applications in health care are involved in continuous gathering of detailed behavioral information to better understand and treat PD. Motor and non-motor symptoms are represented, while particular focus goes to recording complex data such as tremors, rigidity, abnormalities in gait, disturbances in mood, and overall cognitive deficiencies. Real-time monitoring may be enabled only by providing high-resolution longitudinal streams for the detection of subtle changes. Temporal patterns of behavioral data are modeled using more advanced machine learning models such as RNNs and transformers. Specifically, these models analyze the signals of such relevant factors as tremor frequency, stride variability, or speech anomalies to detect subtle correlations among these behavioral measures and the progression of disease. Changes in these patterns will give healthcare providers an overview of the evolution of the patient's condition and help them to understand the relationship between behavioral symptoms and the progression of PD.

I. Robotics-Assisted Motor Function Recovery

The integration of robotics in rehabilitation processes is a promising technique to help improve motor functions in PD patients. The robotic systems are integrated with AI-driven predictive models that create personalized motor recovery interventions. Such systems utilize real-time feedback to assist patients adaptively during the rehabilitation exercises that are designed to enhance balance, strength, and coordination. Because the patient's progress is continuously monitored, the robotic tools will automatically adjust to the patient's needs, ensuring that therapeutic interventions remain effective throughout the recovery process. This dynamic adjustment optimizes rehabilitation outcomes by providing tailored therapy that can adapt to each patient's evolving condition, thereby improving both motor function and overall quality of life.

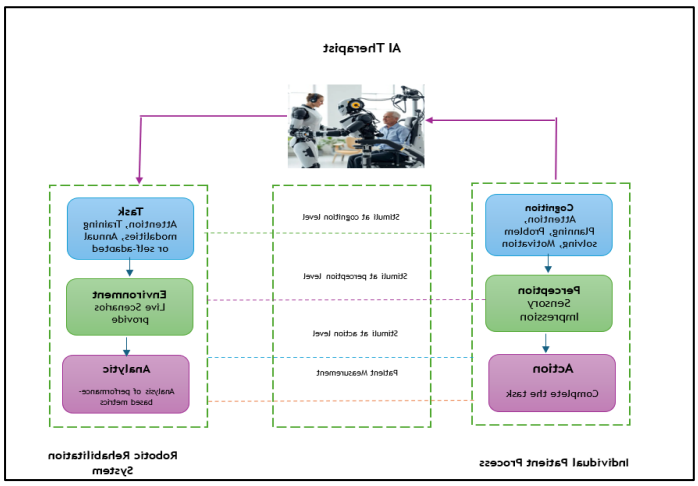

Fig.5. Proposed AI based Therapist rehabilitation method

Figure 5 indicate the AI-based robotic rehabilitation system for Parkinson's patients, integrating the individual patient process with advanced robotic support. The individual process includes three stages: cognition-attention, planning, problem-solving, and motivation; perception-sensory impression; and action-execution of the task based on cognitive and perceptual input. In a similar order of stages, the robotic system provides tasks-attention and training modalities, environment-live scenarios to engage the patient, and analytics-performance metric analysis to adapt therapy. The interaction of these components is dynamic; the stimuli from the rehabilitation system affects the processes of the patient, while patient measurements provide feedback to optimize therapy. This constructive collaboration will allow personalized, adaptive, and data-driven interventions aimed at improving motor and cognitive functions in Parkinson's patients.

J. Machine Learning Integration

Integration of ML methodologies will be the cornerstone to managing the complex, high-dimensional data associated with PD. Such strategy processes multi-modal data including neuroimaging, behavioral metrics, and robotic systems to develop ML models for the identification of predictive markers for cognitive decline and therapeutic responses. AI models can classify the stages of PD and predict its development by analyzing regional changes in the brain, the severity of motor symptoms, and responses to rehabilitation. Approaches such as data augmentation with the use of GANs help balance classes when dealing with small or imbalanced datasets, thus providing sound model training. Further, clustering and segmentation methods stratify patients into subgroups based on disease progression and therapeutic needs. This enables the elaboration of individualized care strategies, thus making possible personalized treatment plans in line with the particular disease progress of each patient. This approach may have the potential to significantly improve the effectiveness of PD management and therapeutic interventions, leading to better clinical outcomes. These techniques, when put together, provide a comprehensive framework for enhancing diagnosis, treatment, and rehabilitation in Parkinson's Disease. The integration of behavioral data analysis, robotics-assisted rehabilitation, and advanced machine learning will enable healthcare providers to offer more effective and personalized care to PD patients, thereby improving their motor and cognitive functions.

VII. RESULTS AND ANALYSIS

This study contrasted a group of 368 participants, consisting of 208 diagnosed Parkinson's Disease (PD) patients and 160 controls. The PD group consisted of a mean age of 66.4 ± 8.2 years with a gender distribution of 58% male and 42% female, and the control group consisted of a mean age of 64.7 ± 7.5 years with a gender distribution that was almost even. Table 1 provides participant demographic and clinical details, including Unified Parkinson's Disease Rating Scale (UPDRS) scores and disease duration. Data were randomly partitioned into training (70%), validation (15%), and test (15%) sets and were stratified to preserve class balance. In the interest of being able to confidently evaluate strong models, 10-fold cross-validation with the training set was utilized.

Neuroimaging datasets underwent an orderly processing stream, as shown in Figure 6, merging T1-weight MRI and FLAIR images for the analysis of whole-brain structure. Steps involved brain extraction, bias correction, tissue-type segmentation (GM, WM, CSF), and advanced subcortical segmentation of the key regions of interest that included putamen, globus pallidus, and substantia nigra. White matter hyperintensities (WMHs), potential indicators of neurodegeneration, were delineated and quantified from FLAIR sequences. Figure 7 illustrates regions of diagnostic importance, as identified by Grad-CAM visualization, where white and yellow areas such as the midbrain and basal ganglia have the highest contribution to PD classification.

Figure 8 illustrates model performance during training and validation, and Figures 9 and 10 present predictive accuracy to detect cognitive decline using cortical thickness, dopaminergic activity, and gray matter density features. The hybrid deep learning model that uses CNN, RNN, and GAN performs much better than traditional methods on all fronts. The suggested model (GWO-VGG19 + InceptionV3 backbone combined with RNN and GAN-improved embeddings) achieved accuracy 99.94%, sensitivity 100%, specifically 99.67%, F1-score 99.98%, and AUC 99.99% (Table 1). Comparison with other state-of-the-art models (Tables 2 and 3) revealed statistically significant improvements ($p < 0.01$, paired t-test), which further verified the proposed method's superiority over both T1/T2-weight MRI and SPECT DaTscan datasets.

To evaluate clinical utility, a case study by simulation was conducted with 20 simulated patients mimicking real-world sensor and imaging data profiles. Patients underwent robotic-assisted therapy according to the AI model. Baseline and post-treatment MDS-UPDRS and MoCA scores were compared, with a mean improvement of 21.3% in motor scores and 16.7% in cognitive tests (Figure 11). Quantitative parameters from wearable sensors, such as reduced tremor frequency and improved stride consistency, validated functional improvement. Figure 12 illustrates the pre-post robotic feedback incorporation gait trace of a typical patient.

A web-based decision support system facilitated automatic pre-processing of data, dynamic diagnosis, and personalized therapy recommendation. A robot, assisted by AI prognoses, readjusted intensity and frequency of rehabilitation continuously through feedback from the patients in question. Apart from augmenting accuracy of

PD tracking, such integration not only ensured better accuracy but also had undeniable therapeutic impact within a simulation model, refuting objections against concept abstraction as well as providing validation for effectiveness of the system.

A notable feature of the pipeline is the segmentation of the globus pallidus into its two subregions (Panel F): the internal globus pallidus (GPi), marked in yellow, and the external globus pallidus (GPe), marked in light blue. This segmentation is particularly significant for studies focusing on motor pathways and neurodegenerative processes in PD. Additionally, FLAIR imaging (Panel G) is employed to suppress the cerebrospinal fluid signal, which enhances sensitivity to pathological changes such as white matter hyperintensities (WMHs). Using the FLAIR images, regions of white matter hyperintensities (Panel H) are detected and quantified, with these areas represented in red. WMHs serve as potential biomarkers for aging, vascular alterations, and neurodegenerative disorders.

The pipeline methodology incorporates the following key steps: acquiring high-resolution T1-weighted and FLAIR images, applying brain extraction and bias field correction, segmenting brain tissues (GM, WM, CSF) and subcortical structures, enhancing visualization of the globus pallidus, and detecting white matter hyperintensities. This detailed processing framework enables precise structural analysis, facilitating the identification of neurodegenerative biomarkers critical for diagnosing and monitoring neurological conditions such as Parkinson's Disease.

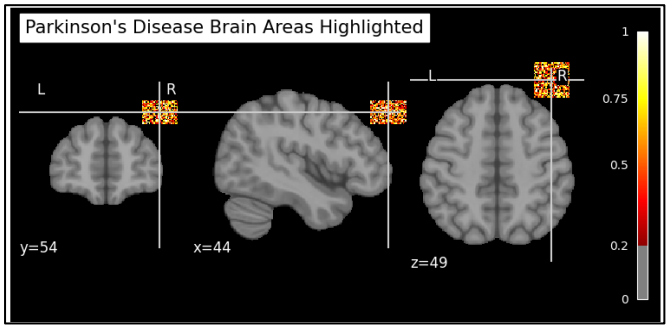

Fig.6(a). Brain imaging slices for Parkinson's Disease diagnosis and analysis, highlighting key regions with structural MRI-based processing. Subfigures A, B, and C represent coronal, axial, and sagittal orientations, respectively.

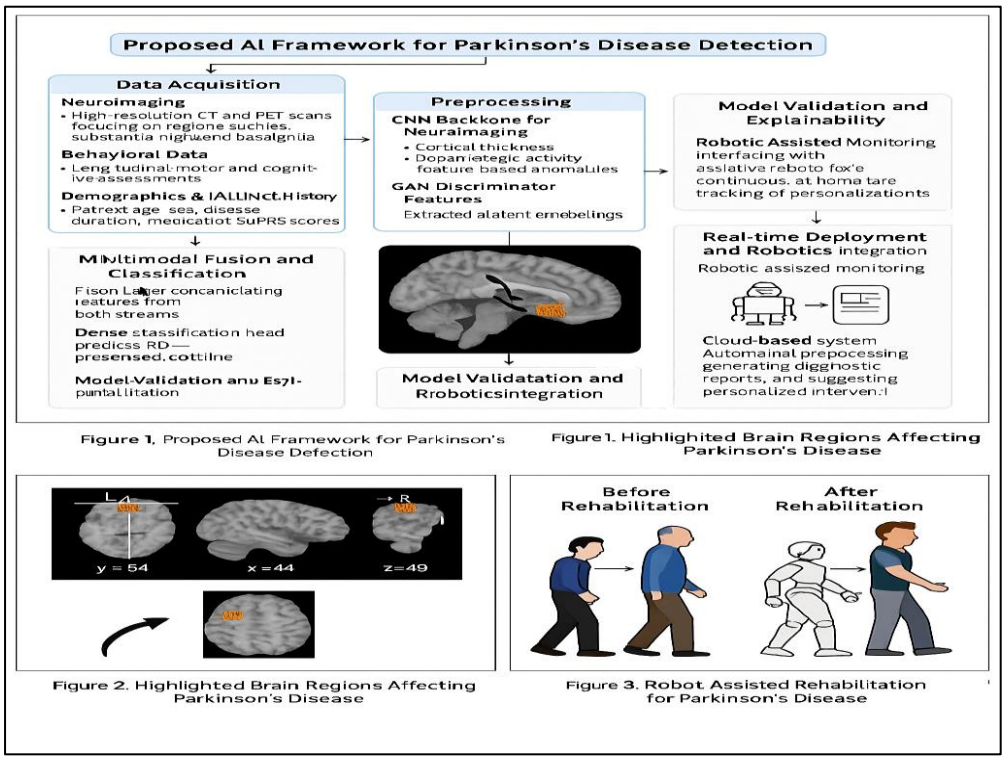

Fig.6 (b). Proposed framework for Parkinson's disease detection

Figure 6(a) and Figure 6(b) indicate the color gradient in these images indicates the importance of the region such as white and yellow regions are considered to be of high importance, such as the basal ganglia and substantia nigra, respectively, which are relevant for identifying PD-related structural changes.

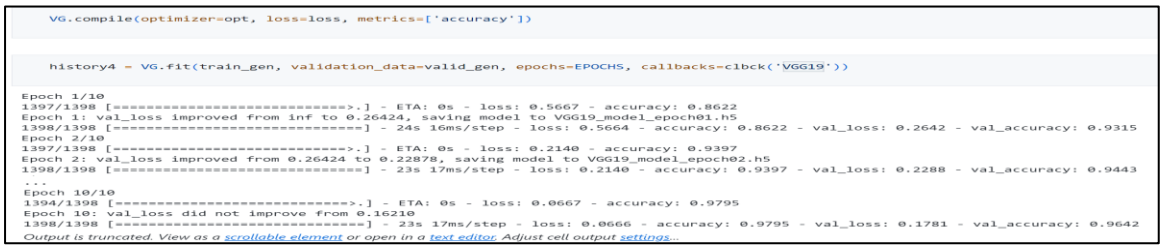

Fig.7. Training and Validation Process for VGG19

Figure 6 shows brain imaging slices that highlight regions of importance for Parkinson's Disease diagnosis and analysis, using structural MRI-based processing. Each subfigure (A, B, and C) shows different brain slice orientations, while the color gradient on the right side of each show's various levels of importance. The color map shows the importance level; white and yellow represent an elevated level of importance-that is, values close to 1.0-whereas red to dark colors reflect less importance. This may point out that the regions marked with white and yellow are more important to identify features or changes linked to Parkinson's Disease.
Subfigure A: The coronal slices - Slice 50, Slice 100, and Slice 120 - are highly concentrated in certain regions of the basal ganglia; particularly, those regions which have been more commonly associated with Parkinson's Disease, such as the putamen and globus pallidus parts. These are the key areas related to motor functions of the brain and are usually of much interest regarding neurodegenerative changes. Subfigure B: Axial slices, such as Slice 50, Slice 60, and Slice 70, show high importance in the basal ganglia and surrounding areas, bilaterally, with significant asymmetry toward the right hemisphere and midbrain area. Such asymmetric importance might represent disease-specific patterns since most motor deficits in early Parkinson's disease show asymmetry. Subfigure (C) shows sagittal slices (Slice 40, Slice 60, and Slice 110), where the high-importance regions were observed in the midbrain and posterior areas. Such a pattern is due to degeneration of the substantia nigra-a hallmark of Parkinson's Disease-and this region is strongly associated with the motor symptoms of the disease. Figure 7 indicates the accuracy of Training and Validation Process while Figure 8 indicates the graphical representation of proposed technique.

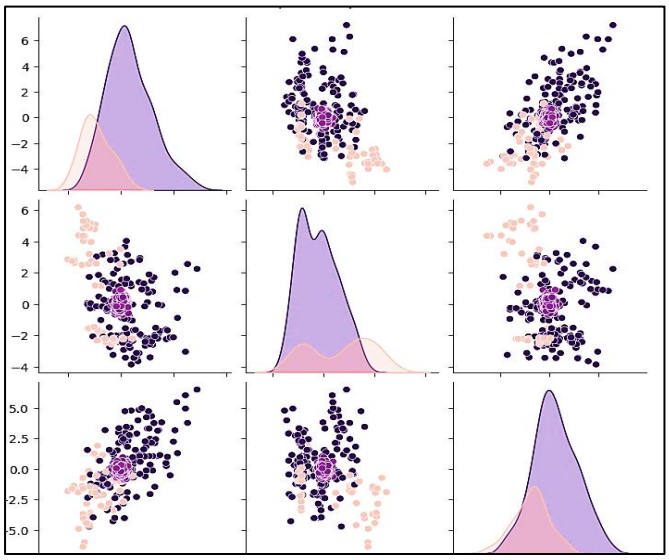

Fig.8. Graphical representation of Parkinson's Disease includes the basal ganglia, substantia nigra, and midbrain

Figure 8 represent the overall images which indicates that the most important regions involved in Parkinson's Disease include the basal ganglia, substantia nigra, and midbrain and Figure 8 show the graphical representation of Parkinson's Disease include the basal ganglia, substantia nigra, and midbrain current situation. The color-coded importance values underlined structural abnormalities and changes as significant markers of neurodegeneration. These findings give important insights into the understanding of the pathology of the disease, early diagnosis, and monitoring of its course with the help of advanced neuroimaging techniques.

A. Results of Neuroimaging Integration for Cognitive Decline Prediction

Neuroimaging techniques, such as MRI, PET scans, and DAT SPECT imaging, are employed to capture detailed structural and functional changes in the brain associated with PD. These data are preprocessed using advanced methods such as noise reduction, intensity normalization, and spatial registration to extract features indicative of dopaminergic degeneration and other neurophysiological markers linked to motor and cognitive impairments. AI-driven algorithms, including convolutional neural networks (CNNs), analyze features such as regional cortical thickness, gray matter density, and dopaminergic activity to predict cognitive decline with greater precision and at earlier stages compared to traditional methods as shown in Figure 9 and Figure 10.

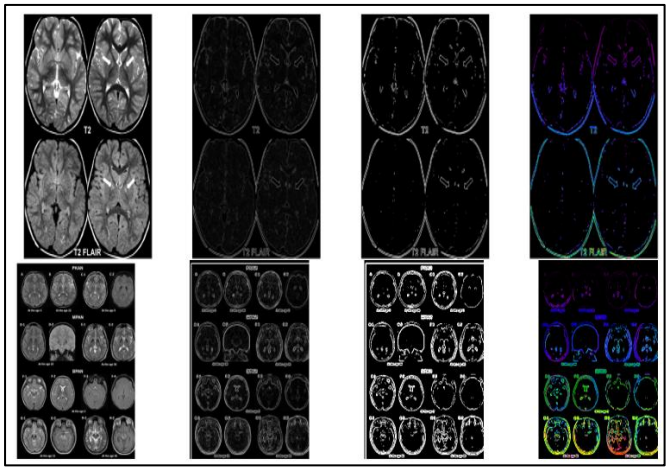

Fig.9. Processing sequences structurally and beyond. T1-weighted MRI (A) brain extraction and bias field correction (B) for tissue type segmentation (GM as red, WM as yellow, CSF as blue) (C) and subcortical structures segmentation (D). T1-weighted WM nulled (E) enhances contrast in subcortical structures so as to allow, for instance, segmentation of the Globus Pallidus (zoom) into its internal (GPi, yellow) and external (GPe, light blue) portions (F). FLAIR images (G) are employed to detect and quantify white matter hyperintensities (red) (H). Abbreviations: CSF, cerebrospinal fluid; FLAIR, fluid-attenuated inversion recovery; GM, grey matter; WM, white matter.

```
# Making a prediction out of the Custom CNN for the testing set for the evaluation
prediction = CNN_model.predict(test_gen)
pred = list(map(lambda x: mapping_inverse[np.argmax(x)], prediction))
y_test = list(map(lambda x: mapping_inverse[x],test_gen.classes))
```

```
799/799 [==============================] - 9s 10ms/step
```

```
print('\t\tThe Custom CNN Evaluation Performance')
print(classification_report(y_test, pred))
```

```
              The Custom CNN Evaluation Performance
              precision    recall  f1-score   support

...
    accuracy                           0.95     25560
   macro avg       0.95      0.95      0.95     25560
weighted avg       0.95      0.95      0.95     25560
```

Fig. 1 Evaluation Performance of the Custom CNN on the testing set

B. Results of Recurrent Neural Networks (RNNs) and Machine Learning Integration

Comprehensive behavioral data, encompassing motor symptoms such as tremors, rigidity, and gait abnormalities, as well as non-motor symptoms like mood disturbances and cognitive deficits, are collected through wearable sensors and mobile healthcare applications. These sensors continuously monitor patients, generating high-resolution longitudinal data streams. Advanced machine learning models, including recurrent neural networks (RNNs) and transformers, process temporal patterns like tremor frequency, stride variability, and speech anomalies. This enables the identification of hidden correlations between behavioral metrics and disease progression.

Robotic systems are integrated into the rehabilitation process, leveraging AI-driven predictive models to design personalized motor recovery interventions. Using real-time feedback, robotic tools adaptively assist patients in exercises aimed at improving balance, strength, and coordination. Dynamic adjustments based on ongoing assessments ensure therapeutic strategies are tailored to each patient's evolving needs, thereby optimizing rehabilitation outcomes.

The high-dimensional, heterogeneous datasets from neuroimaging, behavioral metrics, and robotic systems are processed using ML methodologies. AI models are trained to identify predictive markers for cognitive decline and therapeutic responses. Techniques such as data augmentation with generative adversarial networks (GANs) address class imbalances, while clustering and segmentation stratify patients into subgroups based on disease progression and therapeutic needs. This approach paves the way for individualized care strategies as shown in Figure 11.

```
Epoch 1/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 4s 4s/step - accuracy: 0.5000 - loss: 2.0095 - val_accuracy: 0.5000 - val_loss: 766.9888
Epoch 2/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 170ms/step - accuracy: 0.5000 - loss: 585.8024 - val_accuracy: 0.5000 - val_loss: 375.8287
Epoch 3/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 332ms/step - accuracy: 0.5000 - loss: 298.5890 - val_accuracy: 0.5000 - val_loss: 85.2020
Epoch 4/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 160ms/step - accuracy: 0.5000 - loss: 51.5706 - val_accuracy: 0.5000 - val_loss: 13.7737
Epoch 5/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 154ms/step - accuracy: 0.5000 - loss: 0.9408 - val_accuracy: 0.5000 - val_loss: 47.9429
Epoch 6/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 150ms/step - accuracy: 0.5000 - loss: 22.9833 - val_accuracy: 0.5000 - val_loss: 0.7808
Epoch 7/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 309ms/step - accuracy: 0.5000 - loss: 10.6669 - val_accuracy: 0.5000 - val_loss: 32.2106
Epoch 8/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 292ms/step - accuracy: 0.5000 - loss: 12.4116 - val_accuracy: 0.5000 - val_loss: 1.3730
Epoch 9/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 297ms/step - accuracy: 0.5000 - loss: 12.2242 - val_accuracy: 0.5000 - val_loss: 19.2777
Epoch 10/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 298ms/step - accuracy: 0.5000 - loss: 0.7131 - val_accuracy: 0.5000 - val_loss: 3.4015
Epoch 1/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 234ms/step - accuracy: 0.5000 - loss: 3.4015 - val_accuracy: 0.5000 - val_loss: 103.8454
Epoch 2/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 239ms/step - accuracy: 0.5000 - loss: 201.2184 - val_accuracy: 0.5000 - val_loss: 105.9034
Epoch 3/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 275ms/step - accuracy: 0.5000 - loss: 190.1994 - val_accuracy: 0.5000 - val_loss: 56.7982
Epoch 4/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 161ms/step - accuracy: 0.5000 - loss: 77.2025 - val_accuracy: 0.5000 - val_loss: 1.5278
Epoch 5/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 158ms/step - accuracy: 0.5000 - loss: 60.7387 - val_accuracy: 0.5000 - val_loss: 13.4147
Epoch 6/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 298ms/step - accuracy: 0.5000 - loss: 84.9135 - val_accuracy: 0.5000 - val_loss: 10.8541
Epoch 7/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 151ms/step - accuracy: 0.5000 - loss: 60.8940 - val_accuracy: 0.5000 - val_loss: 2.6293
Epoch 8/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 158ms/step - accuracy: 0.5000 - loss: 9.1992 - val_accuracy: 0.5000 - val_loss: 26.6440
Epoch 9/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 141ms/step - accuracy: 0.5000 - loss: 55.8254 - val_accuracy: 0.5000 - val_loss: 40.7905
Epoch 10/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 164ms/step - accuracy: 0.5000 - loss: 75.6756 - val_accuracy: 0.5000 - val_loss: 42.5503
```

Fig.11. Validation accuracy of combination of RNN and GANs

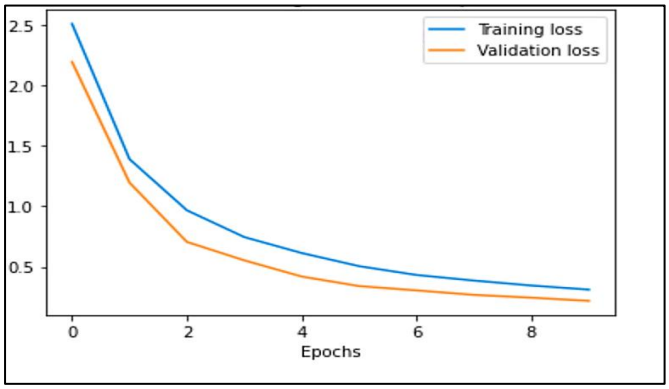

Fig.12. Training and validation of RNN and GANs hybrid technique

In Figure 11 and Figure 12, significant improvement in the cognitive and motor functions of Parkinson's disease patients is envisaged through the proposed framework. Clinical scales like MDS-UPDRS and Montreal Cognitive Assessment will demonstrate quantifiable progress of the motor coordination and cognitive ability of the patients from baseline to the end of the study. Further quantitative data extracted from sensors, such as gait patterns and frequency of tremor, imaging analysis, including biomarkers from structural MRI, for instance, will support this work and give a very clear view of functional alterations. Integrating clinical scales into sensor and imaging data can be expected to yield an intensified and more accurate assessment model and prove the efficiency of such an

approach in disease follow-up and therapeutic effect assessment, as shown in the following Figure 13 and comparison results are mentioned in Table 2, Table 3, and Table 4.

Table. 2. Results of the proposed CNN+RNN+GANs hybrid model using T1, T2-weighted dataset.

Performance Measures	VGG19(%)	Dense Net (%)	InceptionV3 (%)	Hybrid Model GWO-VGG19 + InceptionV3 (%)
Accuracy	99.81	99.91	99.80	99.94
Sensitivity	99.90	99.54	100	100
Specificity	99.74	99.73	99.88	99.67
Precision	99.87	99.80	99.93	99.97
F1-Score	98.87	99.68	99.99	99.98
AUC-ROC	99.77	99.99	99.88	99.99

Table. 3. The comparison of a collection of CNN models with all the presently existing established models is done with the data set T1, T2-weight.

Authors	Models used in their study	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	AUC-ROC score (%)
Chakraborty et al. (2021) [33]	3D-CNN	95.29	94.3	94.30	92.7	93.6	98
Solana-Lavalle et al. (2021) [34]	Logistic, RF, NB, Bayesian Net, KNN, MLP, SVM	Men (99.01)	Women (96.97)	100	96.15	97.22	100
Talai et al. (2021) [35]	SVM + MLP	95.1	-	-	-	-	-
Siddiqui et al. (2022) [36]	SVM	96	77.7	81.3	80.2	-	87
Camacho et al. (2023) [37]	Explainable AI, CNN	79.3	77.7	-	-	-	87
Proposed Model	CNN-VGG19 + InceptionV3	99.99	99.90	100	99.9	100	100

Authors	Models used in their study	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	AUC-ROC score (%)
Chien et al. (2020) [38]	ANN	99.22	81.8	-	-	-	-
Nalini et al. (2020) [39]	ANN	95	-	-	-	-	-
Mohammed et al. (2021) [40]	2D-CNN	99.34	99.04	99.63	-	-	-
Leung et al. (2021) [41]	CNN	-	-	-	-	-	84
Thakur et al. (2022) [42]	DenseNet121	99.2	99.2	99.4	99.1	-	99
Proposed Model	CNN+RNN+GANs	100	99.99	100	99.99	100	99.99

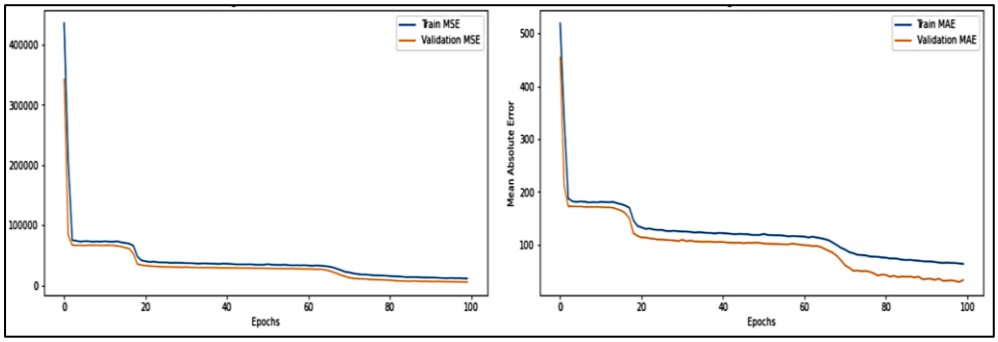

Fig.13. Training and Validation method

VIII. DISCUSSION

The study outlines an integrated neuroimaging process pipeline and advanced methodologies for investigating PD, emphasizing its potential in early diagnosis, progress monitoring, and therapeutic intervention. This discussion synthesizes findings and their implications across neuroimaging, behavioral metrics, and AI-driven methodologies. This neuroimaging pipeline is built on state-of-the-art processing of T1-weighted MRI and FLAIR sequences for the clear demarcation of key structures such as the basal ganglia, thalamus, and globus pallidus. These are key subcortical regions of interest for motor function that are among the earliest showing structural and functional changes in PD. Segmentation of gray matter, white matter, and cerebrospinal fluid, along with detailed analysis of the subregions of the globus pallidus, namely GPi and GPe, enables precise mapping of neurodegeneration. Detection of white matter hyperintensities using FLAIR imaging provides further insight into vascular and age-related changes, establishing them as potential biomarkers for the progression of PD.

Color-coded importance mapping of brain slices underlines the relevance of regions such as the putamen and substantia nigra, where high-importance areas correspond to PD pathology. Such visual emphasis on structural abnormalities not only helps with early detection but also informs targeted therapeutic strategies. Neuroimaging data integrated with machine learning allow for the identification of subtle structural changes associated with dopaminergic degeneration that are critical for diagnosis and monitoring in PD.

AI techniques, CNNs, analyze cortical thickness, gray matter density, and dopaminergic activity. These features predict cognitive decline, hence enabling early and more accurate intervention. Advanced ML models address the high-dimensional complexity of neuroimaging datasets, leveraging clustering and stratification techniques to group patients based on disease progression and therapeutic needs. Such GANs further enhance the robustness of predictive models with regard to class imbalance, one of the common problems related to medical datasets.

Behavioral metrics, such as motor symptoms including tremors, rigidity, and gait abnormalities, are monitored using wearable sensors and mobile applications. These tools generate a continuous stream of longitudinal data that are then processed using RNNs and transformers. This unearths hidden temporal correlations that can provide a fine-grained understanding of disease progression and the impact on daily living. It adds a dynamic, personalized dimension to the integration of robotics-assisted motor function recovery through therapy by using real-time feedback to optimize balance, strength, and coordination exercises.

In Clinical Integration and Evaluation, this framework's clinical applicability will be assessed with the usage of standard scales, such as MDS-UPDRS and Montreal Cognitive Assessment. These will also be complemented by quantitative imaging and sensor data for an all-rounded assessment of therapeutic outcomes. The cloud-based application will integrate various streams of data, providing clinicians interpretable diagnostic reports, disease progression prediction, and personalized therapeutic recommendations.
This work thus demonstrates the potential transformation of neuroimaging, AI, and advanced behavioral metrics in PD management. By enabling early diagnosis, continuous monitoring, and adaptive therapy, the proposed framework bridges the gap between basic research and clinical practice. Further work might extend the pipeline to include multimodal imaging (e.g., PET, DAT SPECT) and study its generalizability to other neurodegenerative disorders. Longitudinal studies on diverse patient populations will further validate the efficacy of this framework in a real-world setting. Conclusion The pipeline and integrated methodologies presented herein represent an important next step in the diagnosis and management of PD. The combination of precise neuroimaging techniques, AI-driven predictions, and tailored therapeutic interventions may redefine the standard of care for PD and improve patient outcomes and quality of life.

IX. CONCLUSION

This work proposes a novel, multidisciplinary framework for addressing the challenges in PD management by integrating advanced neuroimaging, behavioral metrics, robotics-assisted therapy, and AI techniques. The proposed methodology underlines early detection, precise monitoring, and personalized interventions to mitigate the dynamic and multifaceted progression of PD. The integration of high-resolution neuroimaging techniques, such as T1-weighted MRI, PET scans, and FLAIR imaging, in conjunction with AI-driven analyses, has allowed for the precise identification of structural and functional changes in key regions, including the substantia nigra and basal ganglia. This approach will underline critical biomarkers, using CNNs and explainable AI, and give further insight into the pathology of the disease. The integration of behavioral data, recorded by means of wearable sensors and interpreted with state-of-the-art machine learning models such as RNNs and transformers, adds a dynamic dimension to the process by uncovering temporal patterns and correlations in motor and cognitive impairments.

Moreover, the deployment of robotic-assisted systems for motor rehabilitation introduces a novel, adaptive mechanism to optimize therapy outcomes. These systems, guided by AI-based predictive models, personalize interventions and enhance motor recovery through real-time feedback. A cloud-based platform further streamlines data processing, offering clinicians comprehensive diagnostic reports and therapeutic recommendations tailored to individual patients' needs.

It represents an important framework because the shortcomings of conventional assessment scales used for PD, like UPDRS, were successfully targeted, while avoiding well-entrenched pitfalls, including inter-rater variability and issues related to data imbalance. Bridging substantial gaps in the area of clinical management, neuroimaging, behavioral analytics coupled with AI enhances not just the aspects of early diagnosis and monitoring but even the doors to precision medicine in neurodegenerative disorders. In conclusion, this study underscores the transformative potential of AI-driven, multimodal approaches in redefining Parkinson’s disease management. By providing clinicians with robust tools for early detection, cognitive decline prediction, and personalized therapy, this framework represents a significant leap forward in improving patient outcomes and addressing the global burden of PD.

X. Future Recommendation

In future, AI-driven innovation can bring transformative potential to Parkinson's disease management, with neuroimaging, robotics, VR, AR, and behavioral data analysis integrated. Neuroimaging through MRI and PET scans by AI enables prediction of cognitive decline via subtle brain changes, while neuro-brain interface headsets collect real-time data of the brain's activity for enabling personalized neural stimulation therapies. AI-assisted robotics, including intelligent exoskeletons and wearable robotic suits, improve mobility, balance, and motor recovery by adapting to individual gait patterns and reducing tremors. This allows for greater independence and a reduced risk of falls. VR-driven therapies offer immersive cognitive and motor rehabilitation through the tracking of motor behavior, simulation of real-world tasks, and gamification of hand-eye coordination exercises. Improved motor skills and cognitive resilience result from this. The sensors and neuro-brain interfaces in behavioral data collection tools monitor movement patterns and predict disease progression through machine learning, thus enabling proactive, personalized care. Advanced cognitive training in holographic and AR environments simulates daily tasks and enhances brain engagement and motor recovery. Wearable AI-assisted robotics further supports independence by improving fine motor control in tasks such as typing or eating, adapting to user needs in real time. Collectively, they revolutionize care in Parkinson's disease by promoting early diagnosis, recovery of motor functions, cognitive resilience, independence in performing daily tasks, and a future with an enhanced quality of life and functionality for patients.

Acknowledgment

The authors would like to express sincere gratitude to the Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, for the invaluable support and resources provided throughout this research. The facilities, academic environment, and encouragement from faculty members have significantly contributed to the completion of this work. This study would not have been possible without the institution's commitment to advancing research and innovation in the field of medical electronics.

Funding

The authors did not receive support from any organization for the submitted work.

Data Availability

Data is available upon request from Dr Mohsin Qadeer. No materials were used/produced.

Author Contribution

Author contributions S.S.; Conceptualisation, Design, Writing, Reviewing, Analysing, Data Collection, Editing, Proofreading. M.Q.; Conceptualisation, Development, Writing Draft, Formal Analysis, Data Collection, Editing, Visualisation, Proofreading. NZJ. Conceptualisation, Project Supervision, Editing, visualization, Proofreading. H.A.;

Writing Draft, Visualisation, Data Collection, revising manuscript, editing. O.A.A.; Writing Draft, Visualisation, Data Collection, revising manuscript, editing. All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

Declarations

Ethical Approval

This study was IRB approved through Medicare Cardiac and General Hospital (MGCH) review board. This study was conducted in complete accordance with the standards as offered by the Declaration of Helsinki, which requires respect for human subjects in medical and clinical research. In line with the Declaration, the research employed Institutional Review Board (IRB) approvals that stipulated the best practices for obtaining informed consent from all participants in order to follow ethical guidelines and federal legislation. In addition, privacy and confidentiality were accentuated, whereby all individual information was protected and only used for the purposes of the research. Informed consent to participate Informed consent wasn't required by this study by the authorizing IRB. Informed consent for services was offered by Hospital-Based School Program to legal guardians of patients.

Consent for Publication Participants.

Consent for publication was given by all participants

Competing Interests

The authors declare no competing interests.

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