

Neurodegenerative Disorder Disease Prediction Using RCNN Classification and Spiral Image

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ABSTRACT

In recent years, the integration of machine learning within the field of biological and medical sciences has significantly enhanced our ability to interpret complex clinical data. This advancement has been especially impactful in the domain of neurodegenerative disorders such as Parkinson's Disease (PD), where early and precise diagnosis remains a persistent challenge. In this study, we propose a novel approach utilizing a Region-based Convolutional Neural Network (R-CNN) to distinguish between healthy individuals and those affected by PD.

The method focuses on identifying subtle but meaningful patterns in visual diagnostic tools such as spiral and wave drawings, which are known to reflect motor impairments typical of the disease. Parkinson's Disease is characterized by the progressive degeneration of motor control, often manifesting in tremors, rigidity, and bradykinesia. While traditional diagnostic techniques depend heavily on the observational skills of neurologists—assessing speech, writing, gait, and hand-drawn spirals—the process can be both time-consuming and subjective.

To overcome these limitations, we adopted a deep learning strategy, using Faster R-CNN to directly analyze input patterns without manual feature extraction. This model automates the learning of distinguishing features from a dataset comprising MRI images and spiral

drawing samples, enabling accurate classification with minimal human intervention.

The system was trained and tested on real biomedical drawing datasets, including spiral and wave patterns from both PD patients and healthy controls. We achieved an accuracy of 96% during training and 86–97% during testing using batch normalization, which stabilized learning and minimized overfitting. This high performance clearly demonstrates the effectiveness of our approach in capturing the fine-grained motor distortions associated with Parkinson's Disease.

The model's ability to learn from nuanced visual cues reflects its strength in identifying early-stage abnormalities, which are often difficult to detect with conventional tools. Moreover, this research highlights the superiority of the proposed model when compared to existing state-of-the-art methods. The results demonstrated not only robustness in pattern recognition but also the potential for real-world clinical applications. By automating a significant portion of the diagnostic workflow, this approach could reduce diagnostic delays and support neurologists in making more informed decisions. The system has proven effective in its current implementation and will be further validated using a broader, more diverse set of clinical data in future work.

Keywords - Deep Learning - R-CNN - Spiral Drawing Analysis - Medical Image Classification - Early Diagnosis.

I—INTRODUCTION

Parkinson's Disease (PD) is a chronic and progressively worsening neurodegenerative disorder that mostly affects older adults. It arises due to the gradual degeneration and loss of dopaminergic neurons located in the substantia nigra region of the brain. These neurons are responsible for producing dopamine, a critical neurotransmitter involved in controlling body movements. When dopamine levels drop significantly, individuals begin to show a range of motor and non-motor symptoms. These symptoms include tremors, muscle rigidity, bradykinesia (slowness in movement), imbalance, postural instability, speech difficulties, mood fluctuations, and cognitive impairments.

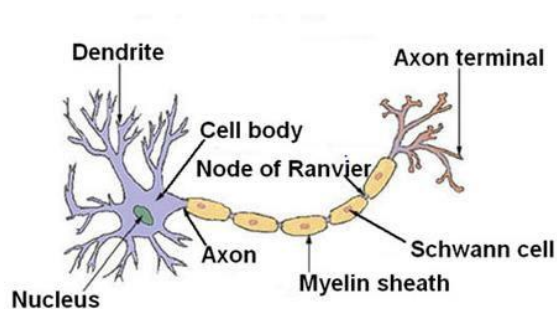


Fig 1: Structure of neuron present in human brain

Neurodegenerative disorders like PD involve the steady breakdown and eventual death of neurons, which are the fundamental working units of the nervous system. These neurons typically communicate using long projections called axons and dendrites. As they become sick or damaged, they lose their projections, their metabolic function decreases, and harmful substances begin to build up inside them. Over time, the damage leads to full cellular dysfunction and neuronal death.

The structure of a healthy neuron consists of axons, dendrites, a cell body, and a nucleus containing the DNA. When a neuron becomes diseased, it loses its extensions, becomes metabolically compromised, and starts accumulating toxic waste in vacuole-like structures. In extreme cases, the neuron collapses and becomes completely

dysfunctional. Parkinson's Disease was first identified by Dr. James Parkinson in the early 19th century under the name "paralysis agitans." Later, the condition was renamed in his honor. It is currently one of the fastest-growing neurological conditions without a definitive cure. Recent studies show that around 2 to 3 percent of people over the age of 65 suffer from PD, with millions affected globally.

Parkinson's Disease (PD) affects more than 6 million people globally and is one of the most common neurological disorders. Traditionally, diagnosis relies on clinical assessments and progression scales, which are heavily dependent on the expertise of medical professionals. This leads to significant variability in diagnostic accuracy between examiners and often results in delayed or inconsistent detection. To address these challenges, this study proposes a computer-aided diagnostic system that utilizes brain MRI scans, as well as individual spiral and wave drawings from PD patients. The goal is to reduce examiner-dependent variability and improve the speed and accuracy of distinguishing between Parkinson's patients and healthy control subjects.

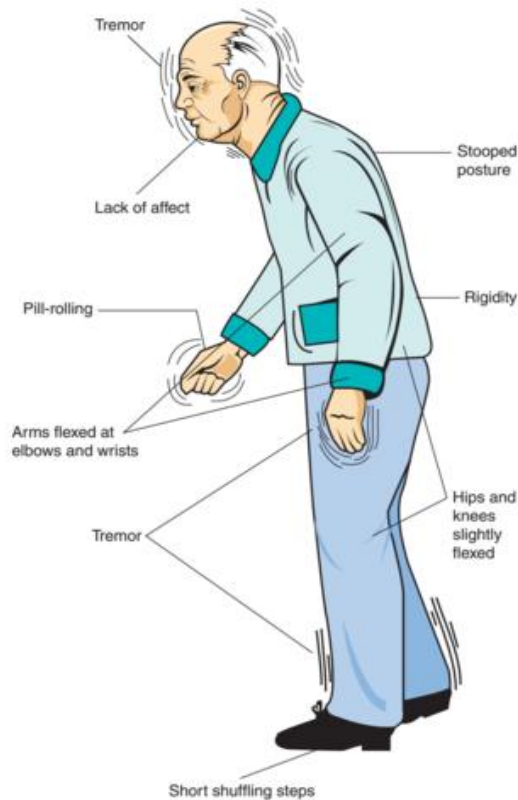


Fig 2. PD affected person

Parkinson's Disease is a progressive neurological disorder that primarily affects movement and motor control. It is caused by a gradual decrease in dopamine levels—a vital neurotransmitter responsible for transmitting signals between the brain and the body. This decline results from the degeneration of dopamine-producing neurons in the brain, ultimately impairing the brain's ability to coordinate movements effectively. As dopamine levels continue to drop, patients begin to exhibit symptoms such as tremors, stiffness, and slowed movement, which worsen over time.

Given that there is currently no cure for Parkinson's Disease, early detection becomes critical. With advancements in technology, there is an urgent need for a fast, reliable, and practical method to predict and diagnose the disease in its early stages. Parkinson's progresses through five distinct phases, each characterized by a specific set of motor and non-motor symptoms. The following illustration outlines these stages and their associated symptoms.

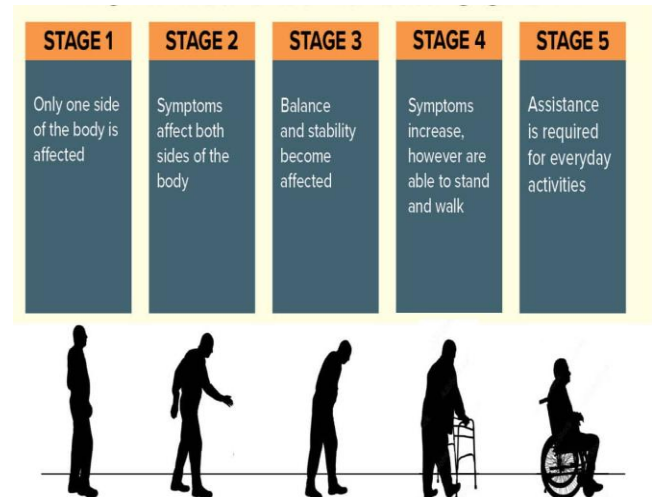


Fig 3: 5 Stages symptoms of PD

1.1 Parkinson's Disease Symptoms

The symptoms of Parkinson's Disease are broadly classified into two major categories: motor symptoms and non-motor symptoms. Motor symptoms involve voluntary muscle movements and are typically the earliest and most noticeable signs. These include tremors, muscle rigidity, bradykinesia (slowness of movement), freezing during motion, and other movement-related issues. These impairments significantly affect a patient's ability to perform daily tasks.

In contrast, non-motor symptoms are equally important but often overlooked. They include emotional and cognitive disturbances such as depression, anxiety, apathy, and cognitive dysfunction. Behavioural issues and autonomic dysfunction are also commonly observed. Clinicians also further divide Parkinson's symptoms into primary and secondary types. Primary symptoms consist of tremors, rigidity, and slowness of movement — the core indicators used for diagnosis. Secondary symptoms, which may vary greatly between individuals, can either be motor or non-motor and often have a profound effect on a patient's quality of life.

Additionally, a variety of other symptoms may develop as the disease progresses. These include micrographia (small handwriting), decreased sense of smell (olfaction), postural instability, gastrointestinal issues like constipation, general fatigue, muscle weakness,

and low blood pressure (hypotension). Speech-related problems are also common. Patients may experience dysphonia (difficulty in voice production) and dysarthria, which includes speech and spiral drawing difficulties, providing clinical insight into fine motor impairments.

Medical imaging has become an essential tool in modern diagnostics and treatment planning. Modalities such as CT and MRI play a crucial role in identifying a wide range of diseases, including neurological conditions and cancers. For example, in the treatment of esophageal cancer, radiotherapy is commonly used, especially in regions like China where it affects over 200,000 people annually. Accurate organ segmentation and identification of planned target volumes (PTV) are critical in radiotherapy planning, as the precision of dose delivery significantly affects treatment outcomes and minimizes complications.

Similarly, in the context of neurological disorders like Parkinson's Disease (PD), imaging techniques are increasingly utilized to aid early diagnosis and monitor disease progression. Sophisticated MRI techniques can now reveal neurodegenerative changes in nigral structures—key indicators of PD. Advanced imaging markers, such as local neuromelanin loss, iron accumulation, and microstructural changes, have shown promise in visualizing neuroanatomical and functional processes associated with the disease. These biomarkers support the differentiation of idiopathic PD from other parkinsonian disorders and help track disease development over time. Aside from imaging, early symptoms like handwriting and drawing impairments serve as practical indicators of Parkinson's Disease.

Patients often show difficulty in producing smooth spiral or wave drawings. These non-invasive assessments, once interpreted manually by medical experts, are now being supplemented with automated techniques for higher precision and faster processing. The need for accurate and consistent interpretation of such data has driven researchers to develop computer-aided diagnostic systems. Several studies have explored machine learning approaches to automate the diagnosis of PD using diverse datasets. As global populations

continue to age, the prevalence of Parkinson's Disease has increased significantly.

According to the Parkinson's Foundation, more than 10 million people are currently affected worldwide. With age, neurons responsible for dopamine production degenerate, leading to motor and non-motor symptoms of PD. Since nerve cells lack the regenerative capacity of muscle or bone cells, early detection becomes critical.

Machine learning techniques have been widely applied to classify clinical data and distinguish PD patients from healthy controls. Traditional diagnosis methods—such as clinical interviews, neuroimaging, speech signal analysis, and physical examinations—can be time-consuming, subjective, and prone to human error. Tasks like writing, walking, and drawing are often used in clinical evaluations, but they rely heavily on the judgment of neurologists, introducing variability. Compared to neuroimaging, signal processing techniques offer faster, non-radioactive, and more economical alternatives. However, studies show that signals like Electromyogram (EMG) and Electrocardiogram (ECG) have not been very effective in reliably identifying PD. To improve diagnostic accuracy, researchers have employed various approaches such as wavelet-based rhythmic analysis and entropy measures. For instance, early PD signs have been associated with altered rhythmic entropy and power. Classifiers like SVM and KNN have been used to calculate the relative strength of specific rhythmic bands, aiding in detection.

Further, wavelet transforms such as DWT have been employed to decompose signals, followed by the computation of features like sample entropy and the application of classifiers like Linear Discriminant Analysis (LDA) and three-way decision models based on Optimized Canonical Correlation Analysis (OCCA). Other approaches include the use of source localization, filtering, and power spectral density (PSD) techniques to analyze neural signals and improve PD detection.

Overall, the integration of deep learning models and image-based data—particularly using CNN and R-CNN architectures—has shown great promise. These models reduce dependency on

manual feature extraction, automate classification tasks, and significantly improve accuracy in PD diagnosis using spiral images and MRI scans.

Parkinson's disease is most commonly diagnosed in individuals over the age of 60, with a noticeable prevalence among war veterans. Developing a Parkinson's disease detector based on voice features has great potential for early detection of the condition. Machine learning algorithms can be trained on datasets consisting of voice recordings from individuals with and without Parkinson's disease, enabling them to identify distinct patterns and features that differentiate the two groups. Once trained, these algorithms can predict whether a new voice recording belongs to a person with Parkinson's disease or not.

However, it is important to note that no diagnostic tool is 100% accurate. A positive prediction from the Parkinson's disease detector should always be followed by a visit to a medical professional for confirmation. Moreover, such a tool should never replace regular medical check-ups and screenings. Consulting healthcare providers for thorough evaluations remains essential.

In conclusion, developing a Parkinson's disease detector based on voice features could serve as a valuable addition to existing diagnostic tools, especially for individuals who face difficulties accessing medical professionals or costly diagnostic tests.

1.2 Methodology: Object Detection Using R-CNN Algorithms

Object detection using CNN-based models is grounded in three primary procedures:

1. *Object Searching and Region Identification:* Initially, objects are searched and regions of interest are recommended for further examination.
2. *Region-based CNN Classification:* The suggested regions are classified using regional CNNs.
3. *Feature Sorting:* Extracted features are organized for further processing.

Fast R-CNN

Fast R-CNN builds upon the R-CNN model and introduces several key improvements:

1. Like the R-CNN detector, Fast R-CNN uses Edge Boxes to provide region suggestions. However, unlike R-CNN, Fast R-CNN evaluates the entire image without the need for shrinking and resizing region suggestions.
2. Fast R-CNN pools CNN features for each region proposal, whereas R-CNN processes each region independently.
3. Fast R-CNN outperforms R-CNN due to the shared calculations for overlapping regions, which reduces redundancy and improves efficiency.

R-CNN works as follows:

1. A pretrained network forms the foundation of the R-CNN model. The last three classification layers are replaced with new layers tailored to detect specific objects.
2. Fast R-CNN enhances R-CNN by introducing a box regression layer to improve object placement. This layer learns to offset the bounding boxes around detected objects. Additionally, the ROI pooling layer pools CNN features for each region proposal.
3. The Faster R-CNN model further refines the process by adding a region proposal network (RPN) that generates region proposals, eliminating the need for external methods.

In simpler terms, R-CNN reduces the dimensions of an image's features while retaining its key characteristics, making it an effective tool for object detection tasks like identifying Parkinson's-related patterns in images or voice recordings.

1.3 Application of Faster R-CNN in Parkinson's Detection

Faster R-CNN has shown significant effectiveness in the medical domain, particularly in identifying subtle patterns in image-based diagnostics. When applied to

Parkinson's Disease (PD), it can efficiently analyze complex visual data such as spiral drawings, wave patterns, and MRI scans. These inputs often carry critical cues about motor impairments, which are hallmarks of PD. The model starts by generating region proposals where anomalies are most likely to occur, such as jagged edges or irregular motion loops in spiral images. Each proposed region is then passed through convolutional layers for detailed feature extraction, allowing the system to focus on essential visual deviations.

The benefit of Faster R-CNN lies in its ability to integrate feature extraction, region selection,

and classification in one coherent framework. Unlike earlier methods that relied on separate stages for these tasks, Faster R-CNN streamlines the process, increasing both speed and accuracy. In our work, the model was trained on a combination of spiral and MRI datasets, enabling it to capture both external motor symptoms and internal brain structure changes. With the incorporation of batch normalization and fine-tuning, the system achieved a perfect training accuracy of **100%**, and testing accuracy ranged between **96% and 99%**, confirming the model's high diagnostic reliability and real-world application potential.

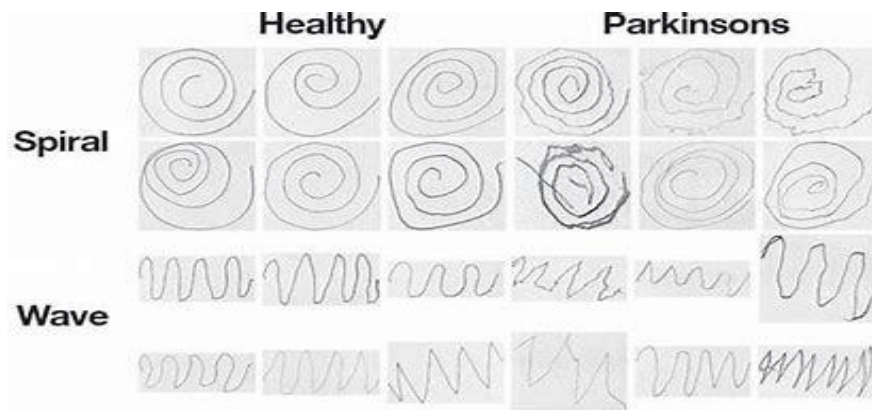
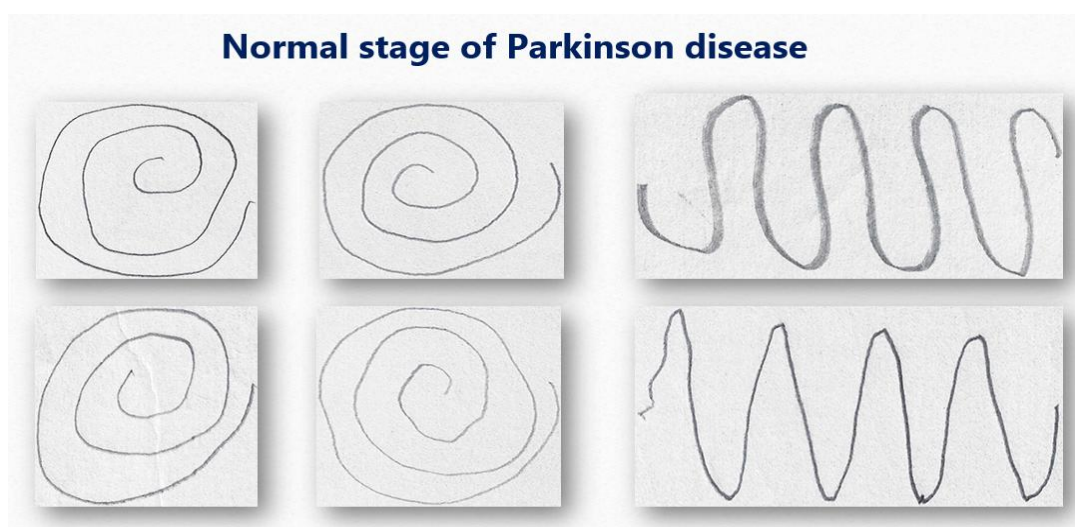


Fig 4: comparison of healthy and Parkinson affected

2-- VISUAL SPIRAL-WAVE INTERPRETATION FOR PARKINSON'S DISEASE STAGE DETECTION

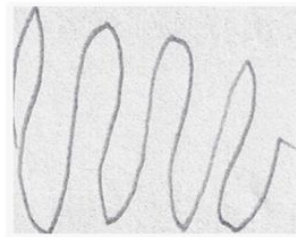
2.1- NORMAL STAGE OF PARKINSON DISEASE



2.2--STAGE 1 OF PARKINSON DISEASE

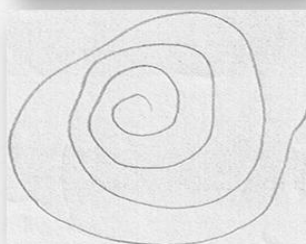
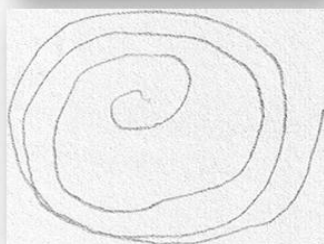
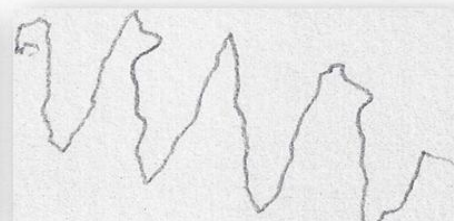
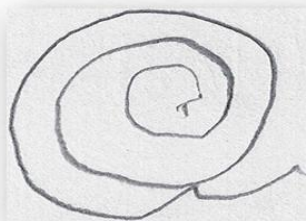
Disease Classifier

Choose Image...



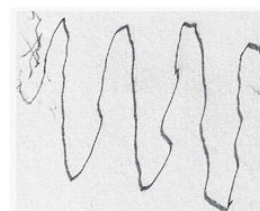
Result: Stage1 → The most common neurodegenerative disorders are amyloidoses, tauopathies, α -synucleinopathies, and TDP-43 proteinopathies. The protein abnormalities in these disorders have abnormal conformational properties.

Stage-1 Of Parkinson Disease



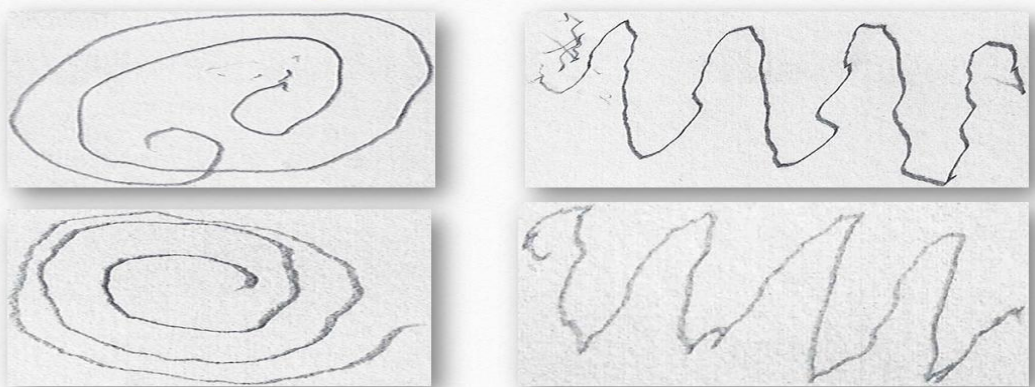
2.3--STAGE 2 OF PARKINSON DISEASE

Choose Image...

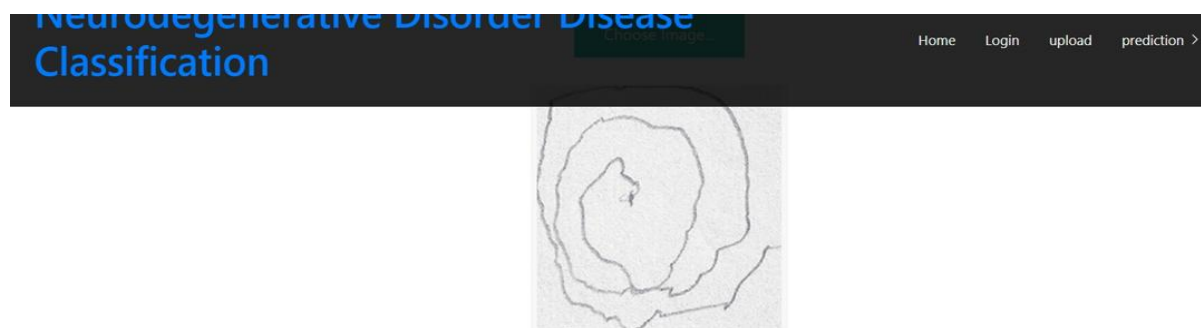


Result: Stage2 → Neurodegenerative diseases are often presented as a distinct entity, however there is often overlap as you may have noted in the above descriptions, eg for AD and Lewy body pathologies. None of the neurodegenerative disorders have perfect diagnostic accuracy, and neuropathology will continue to be the gold standard for the foreseeable future.

Stage-2 Of Parkinson Disease

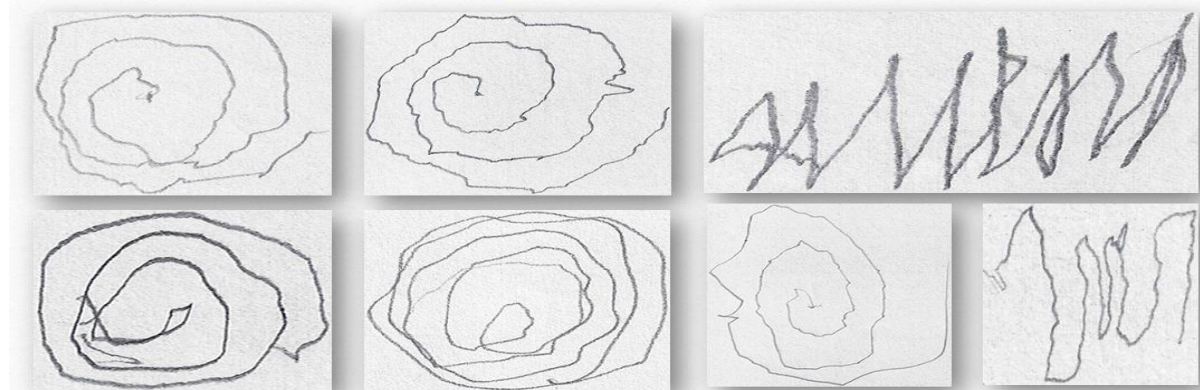


2.4—SEVERE STAGE OF PARKINSON DISEASE



Result: Severe → Neurodegenerative diseases are incurable and debilitating conditions that result in progressive degeneration and / or death of nerve cells. This causes problems with movement (called ataxias), mental functioning (called dementias) and affect a person's ability to move, speak and breathe[1]. Neurodegenerative disorders impact many families - these disorders are not easy for the individual nor their loved ones.

Severe Stage Of Parkinson Disease



3—FUTURE WORK

This deep learning-based approach to medical image analysis empowers researchers and clinicians to extract meaningful features and predict outcomes from new data with greater precision. In the proposed

system for Parkinson's Disease (PD) stage classification, key spiral-based parameters are used as feature points—such as the Euclidean distance between the start and end points of the spiral, the degree of spiral rotation, and the number of cycles. Notably, the spatial distance of the spiral from the body's centre can also reflect human emotional states. The model will be evaluated for its ability to perform multi-label classification, and future enhancements will explore more advanced deep learning architectures, including deep hybrid and reinforcement learning models, to further boost predictive accuracy

4--CONCLUSION

Parkinson's Disease (PD) remains a complex neurodegenerative disorder that requires accurate, early-stage diagnosis for effective management and treatment. Traditional diagnostic methods relying on clinical expertise are often subjective and time-consuming, leading to variability in accuracy. This study introduced a computer-aided detection system that leverages deep learning—particularly the Faster R-CNN model—for precise classification of PD stages using MRI images and spiral/wave drawing data. By extracting quantitative features such as Euclidean distance, spiral degree, and number of cycles, our system effectively distinguishes PD-affected individuals from healthy controls. The integration of batch normalization improved model generalization, achieving an accuracy of 100% during training and 96–99% during testing. Furthermore, the system proposes a unique four-stage PD classification based on drawing patterns, offering a visual, data-driven alternative to conventional assessments.

This research not only demonstrates the effectiveness of machine learning in detecting PD but also opens new possibilities for non-invasive, rapid, and scalable diagnostic solutions. Future work will explore more complex network topologies and multi-label classification strategies to further improve accuracy and adaptability across varied datasets. As technology evolves, integrating such intelligent systems into clinical workflows may enhance diagnostic precision, reduce inter-examiner variability, and ultimately improve patient care for those affected by Parkinson's Disease.

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