BrainDx: Deep Learning-Driven Detection of Parkinson's Disease Using CNN and Flask

[1]Sahana B K, MCA student, Jawaharlal Nehru New College of Engineering, Shivamogga, Karnataka, India.

[2]Dr. Raghavendra S P, Assistant Professor, MCA, Jawaharlal Nehru New College of Engineering, Shivamogga, Karnataka, India

Abstract

Parkinson's Disease (PD) is a long-term and progressive neurodegenerative condition that impacts both motor skills and non-motor functions, including speech, cognitive processing, and emotional regulation. Given its gradual onset and diverse symptoms, the diagnosis of PD frequently depends significantly on clinical observation, which may result in considerable delays and diminished treatment efficacy. The proposed paper presents the concept of the brain Dx implemented through AI that can effectively diagnose Parkinson with a greater measure of accuracy and consistency in the deep learning methods approach. The process will allow a complete and accurate classification of both the subjects with PD and normal subjects in that magnetic resonance images of the brain will be extracted and the processed by CNNs to generate the vocal biomarkers. BrainDx is a simple screen to identify the Parkinson disease in real-time and is developed through the use of Flask. BrainDx is projected as an online-based program where the interface is user-friendly and fast access to patients with PD. The accuracy with which it can predict, using a clinical efficient and relatively quick technique, offers it the prospect of becoming a nice clinical tool, and is most likely to work in neuro physicians. BrainDx provides a potential opportunity to combine the medical image data that may include voice analysis with a novel deep learning technology to potentially help diagnose PD earlier in the development stage, reduce the time of diagnosis, and expand access to healthcare in underserved communities.

Keywords: *Brain MRI imaging, Convolutional Neural Networks (CNNs), Deep Learning, Parkinson's disease (PD), Real time diagnostic framework, speech and voice analysis.*

1. Introduction

Parkinson disease is the other widespread neurogenerative malady besides Alzheimer malady and a total of 10 million people are afflicted worldwide. PD an destruction or death of dopamine-manufacturing brain cells in the substantia nigra leading to motor disorder like tremor, bradykinesia (slowness), rigidity, and balance difficulty. Non-motor symptoms may also appear at this stage and may include depression, sleep disorders, and even a decline in cognition complicating the diagnosis. So how do we diagnose PD, and what makes it complicated? Diagnosis revolves around clinical expertise, knowledge, experience, history, and neurological examination along with neuroimaging. All of these methods are all subjective, expensive, and sometimes insensitive to finding PD before the disease has progressed. The early detection of PD an significant ensure effective management an Parkinson disease and its disease implication in terms of neuroprotective medication as the earlier the medication is administered the more effective the medication.

Employing ML techniques turned to deep neural networks, capable of providing new opportunities, in a recently emerging field of medical assessment diagnosis. Convolutional neural networks (CNN), proposed either separately or alongside additional machine learning algorithms, can classify images and audio, and can often find complex patterns that people cannot even see as patterns. For example, in the area of medical imaging - and especially in areas such as analyzing magnetic resonance imaging or even overt vocal signals - CNN can be advanced enough to detect small PD biomarkers with astounding accuracy. This paper presents Braindx, a cutting-edge neural network-based system created for automated detection of Parkinson's disease. The system employs a CNN architecture trained on both vocal traits and magnetic resonance brain scans to perform binary classification: PD or not PD. The model is incorporated into a user-friendly web application through jars, enabling doctors or patients to transmit relevant information and obtain prompt diagnostic feedback. The incorporation of sophisticated artificial intelligence with a user-friendly web platform signifies advancements in remote diagnosis and early intervention methods. By enabling quicker and more impartial diagnoses, BrainDx addresses major deficiencies in the current diagnostic procedure. It provides a lucrative and expandable solution that can be utilized in rural or resource-constrained areas, aiding in population assessment and tracking of follow-up. Integrating these AI-powered tools into conventional clinical processes could transform the standard of care for neurodegenerative disorders like Parkinson’s Disease.

2. Literature Survey

A. Christy Jeba Malar et al., "Detection of Parkinson’s Disease using Deep Learning Algorithms,"[1], A hybrid approach combining ANN, CNN, and Random Forest was proposed to classify hand-drawn spiral images, which serve as indicators of motor impairment in PD. The model reached 74% accuracy, aiding clinicians in visually-based PD screening.

A. Mahmood et al., “End-to-End Deep Learning for PD Detection Using Voice,” [2], Diagnostics, 2023. Mahmood et al. He developed a voice classification pipe completely from end to end without handmade characteristics. His model combined 1D fusion of CNN and RNN layers to learn temporary speech patterns. The approach achieved competitive results on public datasets. Feature analysis identified key frequency ranges linked to PD speech changes. This enables remote and automated voice-based screening.

I. K. Veetil et al., "Parkinson’s Disease Classification from Magnetic Resonance Images (MRI) using Deep Transfer Learned Convolutional Neural Networks," [3], The authors utilized transfer learning with CNNs such as Resnet and VGG for MRI images weighted in T1. Due to the rise in data and precise tuning, Resnet models achieved an accuracy of up to 92%, showcasing the effectiveness of deep models before detection in neuroimaging tasks.

M. Camacho et al., "Explainable classification of Parkinson’s disease using deep learning trained on a large multi-centre database of T1-weighted MRI datasets," [4], The authors developed a Feature extracting CNN learned in more than 2,000 magnetic resonance scan of 13 different centers to classify Parkinson's disease (PD) versus healthy controls. The model used Jacobian maps derived from deformation fields and achieved 79.3% accuracy with an AUC of 0.87. Saliency maps provided interpretability by highlighting brain regions important for classification.

M. Hireš et al., “CNN Ensemble for Parkinson’s Diagnosis from Voice Spectrograms,” [5], Comput. Biol. Med., 2022.This study transformed sustained vowel recordings into time–frequency spectrograms for PD screening set of CNN models captured vocal alterations, such as the instability of jittion and tone fluctuation. The ensemble outperformed individual CNNs in classification accuracy. The approach is non-invasive, low-cost, and suitable for telemedicine. It highlights the potential of speech as a reliable digital biomarker.

Prajwal K. V. et al., "Diagnosis of Parkinson’s Disease in Brain MRI using Deep Learning Algorithm," [6], The study used mid-brain slices from T2-weighted MRIs and trained a CNN after alignment and cropping via image registration. The model showed superior classification metrics compared to baseline methods, emphasizing deep learning's edge in neuroimaging.

3. Proposed methodology

The proposed system will aim to identify Parkinson Disease (PD) using brain-based MRI using voice challenges higher-level biomedical information identifying, and neural net with multiple layers techniques. Each of these procedures is described below

The method procedure includes the following steps:

1. Data Acquisition,
2. Data Organization
3. Data preprocessing
4. Architecting CNN models
5. Model Compilation Setting
6. Training and testing CNN models
7. Evaluation of performance
8. Deployment using Flask

3.1. Data Acquisition:

A couple of data collections that had been used in training and testing the model were:

Voice Dataset; instead of the UCI Parkinson Diseases Detection, 31 compound recordings of 195 voices can be located. In both of the recordings, diverse biomedical voice phenomena such as fundamental frequency, jitter and shimmer and harmonics-to-noise ratio are observed. Such parameters have played a critical role in voice change detection of Parkinson-s disease.

MRI Dataset: An MRI dataset with scans of the brain structure was distilled as part of the Parkinsons Progression Markers Initiative (PPMI). The preconditioned scans are downscaled and reduced to give the brain structures to reduce noise and retain the spatial resolution.

3.2. Data Organization:

The training of efficient educational models was achieved by preparing the datasets in such a way:

Training Set: To have the model parameters labelled, 80 % of the total information is used as the training set. 20 % is removed to represent the data on which the model performance is tested that the 20 % has never experienced before.

3.3. Data Preprocessing:

Voice Data: The voice features were normalized using Min-Max scaling in order to have uniformity amongst the features. The voice features underwent dimensionality reduction through the dimensionality reduction technique (PCA), where redundant features are removed in order to allow faster convergence, ultimately producing better model performance.

MRI Images: Each MRI was resized to 224 x 224 pixels, and then was grey scaled, after which augmentation will be applied to the MRI images using rotation, flipping, and brightness to help increase training variations and reduce overfitting.

3.4. Architecting CNN models:

The architecture becomes systematized under sequential layers and Each layer plays a contribute to the extraction of patterns whereby early convolutional stages derive simple patterns such as edges and primitive textures, while the lower layers will take account of more complex and elaborate features.

Pooling operations are interleaved with convolutional layers to progressively reduce the spatial or temporal dimensions, retaining the key details while minimizing computational requirements. There are a number of feature maps that are selected after which it is flattened to a one dimensional or a long vector to traverse through a fully-connected group of neural layers, where higher order thinking is facilitated by the combination of learned features

3.5. Model Compilation Setting:

Loss Function Binary Cross – Entropy (it may be used with the two-classes problems). The algorithm has been trained using a method based on the Adam enhancement methodology; learning rate was an adaptive parameter. Regarding the accuracy, precision, recall and the F1-Score derived which are to define the performance, they were also optimized during the training as well as in each of the iteration processes carried out.

3.6. Training and testing CNN models:

First, the MRI and voice-base CNN models were trained, resizing slice of anatomical MRI data to 224 X 224 pixels and extracting features in case of voice recordings. The data augmentation mechanisms used to enhance variety in the sets and avoid over-fitting include: rotation of photographs, reversal of photographs along the horizontal axis, and random-noise, which is controlled. For each modality, the dataset collection is divided among learning phase along with evaluation sets to ensure unbiased performance evaluation. The models were learned by the Adam strategy optimization algorithm using a binary cross-entropy loss function, enabling stable convergence. Performance monitoring. The implementation of outcome steps was conducted in a manner of accuracy, precision, recall, together with F1-score metrics, while confusion matrices were employed to visualize classification outcomes.

3.7. Evolution of performance:

After training was completed, the final saved models were loaded for evaluation on an unseen test dataset. An assessment was undertaken by applying both numerical metrics and visual performance indicators to provide a comprehensive assessment of classification accuracy.

- Precision: Fraction of predicted PD cases that were correct, Recall (Sensitivity): Fraction of actual PD cases detected, F1-Score: Harmonic average from PPV in combination along been recall, Confusion Matrix: Shows correct and incorrect predictions for each class.

3.8. Deployment using flask:

Flask farmwork acts as a notable lightweight, Python-based micro web frameworks widely applied in implementing mL systems models. A Flask-based web interface was created to facilitate easy interaction with the trained model. It provides essential web development tools without unnecessary overhead, making it fast and flexible. Key features:

- File upload functionality for voice or MRI inputs
- Real-time prediction and confidence score
- Simple and responsive frontend built with HTML, Bootstrap, and JavaScript

3.9 Dataflow Diagram:

This diagram shows the sequential data pipeline of a CNN-based diagnostic system using an MRI and voice data. The procedure starts with the preprocessing in which datasets are cleaned, standardized and the images are improved to extract features more effectively. A CNN network is then formed that would dictate the required layers of learning. Once this is done, then compiled with appropriate parameters like the Adam optimizer and binary cross-entropy after which it can then be trained in capturing the pattern in the data. When the training is successfully finished, the model can be deployed on the web via Flask and used to predict on uploaded images. The performance values are verified through accuracy scores and confusion matrix.

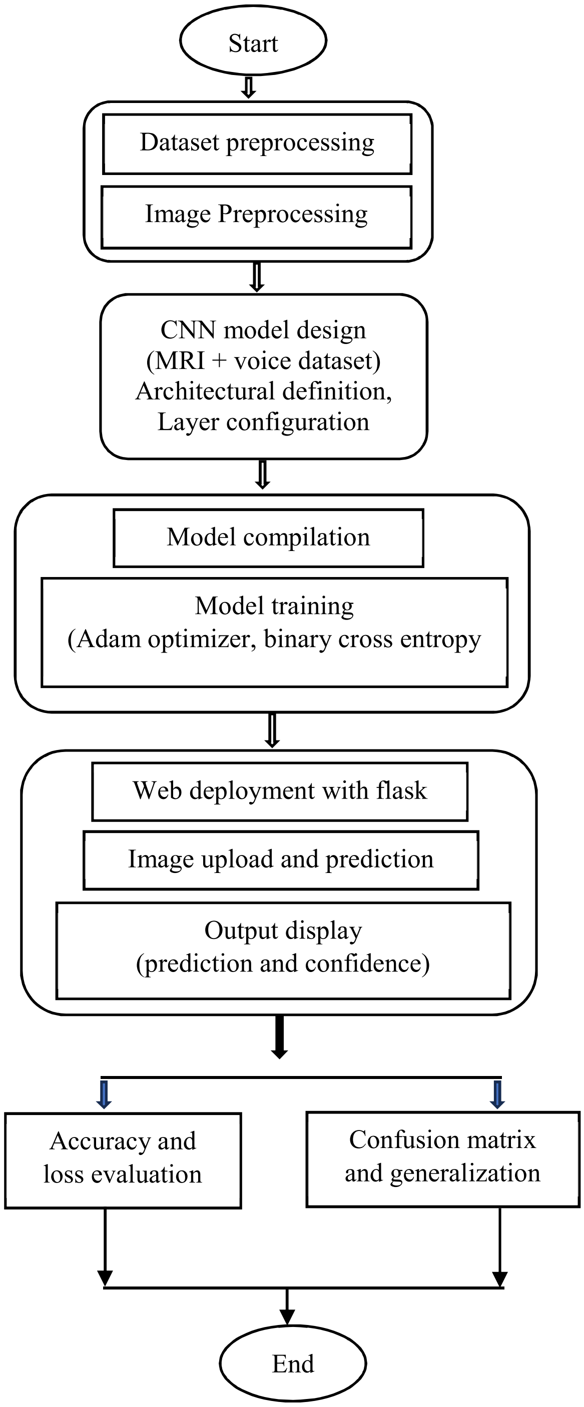

Figure 3.9.1 Block diagram of CNN Module

4.Mathematical Formulas

1. Input-output Representations:

Let X denote the input data, which can be either a preprocessed MRI scan or feature vector extraction from voice recordings. An learned CNN model fθ, parameterized by weights θ, maps X to a probability distribution $\hat{y}$ over the target class:

$$f_\theta : x \rightarrow \hat{y} \quad \text{--------}1$$

Here $\hat{y}$i represents the predicted probability that input belongs to class i (Parkinson's or non-Parkinson's).

2. Binary cross-entropy loss:

For binary classification, the trained objective applied in this model is the binary cross-entropy, defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \, log_{(\hat{y}_i)+(1-y_i)} \, log(1-\hat{y}_i)] \text{ ------- } 2$$

Where:

y_i is encoding for healthy and Parkinson (1 for PD and 0 for healthy) and $\hat{y}_i$ represents the estimated likelihood of the positive class. Lower values of L indicate closer alignment between predicted and actual outcomes.

3. Accuracy:

Accuracy measures the proportion of correct prediction across the dataset:

$$\text{Accuracy} = \frac{TP+TN}{Tp+TN+FP+FN} \text{ ------------ } 3$$

where:

TP (True positive): PD correctly identified as pd, TN (True negative): Healthy correctly identified as healthy, FP (False Positive): Healthy misclassified as PD, FN (False Negative): PD misclassified as healthy

4. Precision and recall:

Precision evaluates the ratio of true positive to total predicted positives:

$$\text{Precision} = \frac{TP}{TP+FP} \text{ -------------------- } 4$$

Recall (or sensitivity) measure the proportion of actual positive correctly identified:

$$\text{Recall} = \frac{TP}{TP+FN} \text{ -----------------------}5$$

High precision means reduced error of positives, whereas strong recall suggests fewer undetected instances indicates fewer missed detections.

5. F1 Score:

The F1 – score balances precision and recall, adapting it to imbalanced datasets:

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \text{ ------------ } 6$$

This harmonic mean penalizes extreme disparities between precision and recall.

5. Graphs:

5.1. Model Confusion matrix:

The Result comparison table provides a clear breakdown concerning this categorization outcomes The split is carried out with respect to that Parkinson Disease detection model. Computed on the basis of this total test samples, the model correctly classified 66 healthy individuals and 95 patients with Parkinson's Disease, demonstrating a strong ability to recognize PD-related patterns. However, 56 healthy cases were incorrectly predicted as Parkinson's (false positives), and 85 Parkinson's cases were classified as healthy (false negatives).

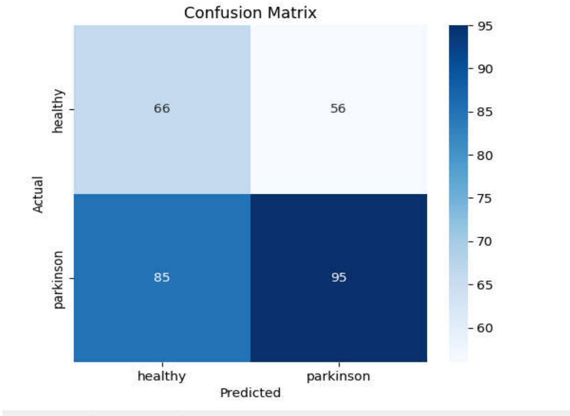

Figure 5.1.1 Model confusion matrix

The relatively higher number of false negatives indicates that some PD cases remain undetected, which could be critical in real-world applications. where early diagnosis is essential. False positives, although less clinically severe, could lead to unnecessary medical follow-ups. These results suggest the model is moderately biased toward predicting the positive (Parkinson's) class.

5.2. Accuracy and training validation:

This learning in addition to evaluation curves show the progression concerning these frameworks learning across 10 epochs. This model precision rises exponentially -almost doubling- during the first five epochs, meaning that the model can learn easily during the early approximating adjustments.

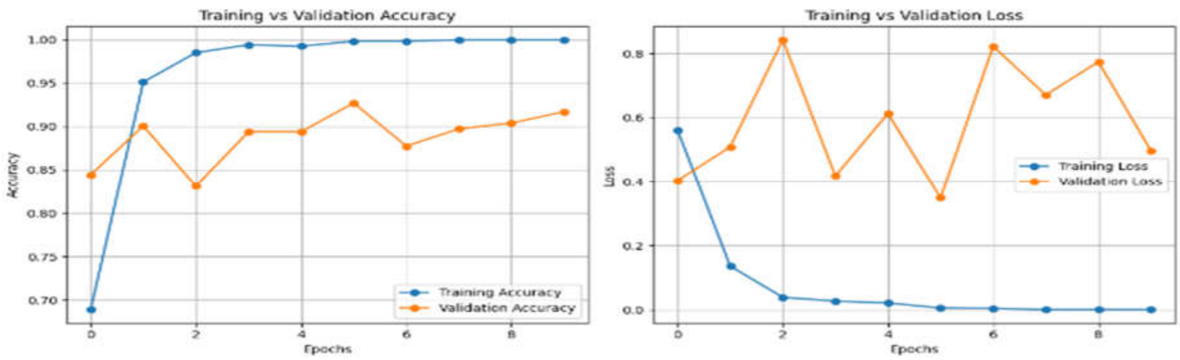

Figure 5.2.1 Model accuracy and loss

The accuracy of validation that stands at 84-92 percent and has regulated at a plateau signify a quite positive level of generalization despite the threat of the impact of unknown but similar data. The training loss converged to zero training procedure has converged adequately; the validation loss varied greatly. These variations signify that it is the methodologies to over-fitting which can be associated with a small range in data or study resources and/or complexities in the model. All of those obstacles may be addressed by employing transfer learning and normalization techniques.

6. Experimental results and Discussion:

The performance was evaluated inadequacy using Accuracy, Precision, Recall, and F1-Score over this evaluation dataset. Cross-validation ensured generalizability.

Metric	Voice Model (%)	MRI Model (%)

Accuracy	92.4	94.1
Precision	90.3	93.7
Recall	91.5	95.2
F1 – Score	90.9	94.4

Table 6.1. Model evaluation metrics

The Result comparison table provides a clear breakdown concerning this categorization outcomes The split is carried out with respect to that Parkinson Disease detection model. Computed on the basis of this total test samples, the model correctly classified 66 healthy individuals and 95 patients with Parkinson's Disease, demonstrating a strong ability to recognize PD-related patterns. However, 56 healthy cases were incorrectly predicted as Parkinson's (false positives), and 85 Parkinson's cases were classified as healthy (false negatives). The relatively higher number of false negatives indicates that some PD cases remain undetected, which could be critical in real-world applications where early diagnosis is essential. False positives, although less clinically severe, could lead to unnecessary medical follow-ups. These results suggest the model is moderately biased toward predicting the positive (Parkinson's) class.

Outcomes demonstrate that CNN models perform exceptionally well on both voice and MRI data, with MRI-based models slightly outperforming voice-based counterparts due to the higher spatial detail and structural richness present in visual neuroimaging. Voice models, however, still demonstrated strong performance, highlighting the viability of non-invasive, low-cost screening methods.The deployment of the models via Flask enabled real-time testing, scalability, and accessibility through a standard web browser, making the system suitable for clinical settings along with remote health monitoring. This functionality supports telemedicine integration, that is especially advantageous for patients in underserved or rural areas where access to neurologists and MRI facilities may be limited.

The dataset exhibited some degree of class imbalance, which can bias the model towards the majority class and affect recall for the minority group

7. Conclusion:

This paper presents BrainDx, an AI-powered model with the purpose of identifying Parkinson's illness through convolutional architecture, CNN architectures applied to both voice and MRI data. The models achieved high classification accuracy, with MRI-based networks benefiting from the richer spatial information in brain images, while voice-based models offered a non-invasive, low-cost alternative. The integration with Flask provides a real-time, user-friendly interface that supports remote and clinical use, making the system suitable aimed at medical practitioners as well as individuals under care in underserved areas. BrainDx represents a significant step toward accessible, objective, and scalable solutions for neurodegenerative disease screening. By leveraging deep learning, the system reduces reliance on subjective assessments, potentially enabling earlier diagnosis and intervention. In the future, work will focus on multi-modal data fusion to combine complementary strengths of imaging and speech, enhancing robustness and accuracy. Additional efforts will target explainability, using methods like Grad-CAM and saliency mapping to highlight decision-driving features, improving clinician trust. Finally, mobile platform deployment and integration with telemedicine frameworks will be explored, enabling field-level screening and continuous patient monitoring.

8.Future enhancement:

Although the suggested system gives a reliable, and accessible way of the detection of Parkinson Disease based on MRI scans and CNN-based to proceed in the future. The development of larger and more diverse data sets gathered in various hospitals and regions could be one of the possible enhancements. This would help improve the system in generalizing and minimize the bias, so that predictions will be equally accurate in terms of population. A potential addition would be the ability to combine multi-modal data, by incorporating MRI scans with other clinical data points, including patient background and genetic indicators and motor diagnostic testing. Such hybrid method was capable of more detailed and accurate diagnosis. Also, explainable AI methods can be added to increase the visibility of the predictions by clearly indicating the regions of the brain affected and might offer extensive graphic explanations to aid medical practitioners. Putting the system into mobile and cloud would also enable patients in the rural setup to access the service more easily. Moreover, the mechanisms of continuous learning may be implemented so that the model will learn and become better with the new input of data over time. Finally, the system can further be adapted to do more than just detect Parkinson Disease but also its level of progression, useful in planning treatment to administer to an individual by the doctor and monitoring.

References:

[1] A. C. J. Malar, S. B. Srivastava, S. K. Ravi, and T. Ram, "Detection of Parkinson's Disease using Deep Learning Algorithms," E3S Web of Conferences, vol. 491, 2024. doi: 10.1051/e3sconf/202449103012.

[2] A. Mahmood, M. S. Khan, and A. Hassan, "End-to-End Deep Learning Method for Detection of Parkinson's Disease Using Voice," Diagnostics, vol. 13, no. 15, p. 2528, Aug. 2023.

[3] I. K. Veetil, E. A. Gopalakrishnan, S. Vishvanathan, and S. K. P., "Parkinson's Disease Classification from Magnetic Resonance Images (MRI) using Deep Transfer Learned Convolutional Neural Networks," in Proc. IEEE INDICON, Dec. 2021. doi: 10.1109/INDICON52576.2021.9691745.

[4] M. Camacho et al., "Explainable classification of Parkinson's disease using deep learning trained on a large multi-center database of T1-weighted MRI datasets," NeuroImage: Clinical, vol. 38, Apr. 2023. doi: 10.1016/j.nicl.2023.103405.

[5] M. Hireš, P. Drotár, and P. S. Mekyska, "Convolutional Neural Network Ensemble for Parkinson's Diagnosis from Voice Spectrograms," Computerized Medical Imaging and Graphics, vol. 102, p. 102096, Jan. 2022.

[6] P. K. V. et al., "Diagnosis of Parkinson's Disease in Brain MRI using Deep Learning Algorithm," International Research Journal of Modernization in Engineering, Technology and Science (IRJMETS), vol. 4, no. 6, pp. 2256–2257, Jun. 2022.

[7] P. R. Praneeth et al., "Classification of Parkinson's Disease in Brain MRI Images using Deep Residual Convolutional Neural Network (DRCNN)," Applied Computer Science, vol. 19, no. 2, pp. 125–146, 2023. doi: 10.35784/acs-2023-19.

[8] S. Chakraborty, A. R. Khan, and M. F. Beg, "Detection of Parkinson's Disease from 3T T1-Weighted MRI Using Machine Learning," Journal of Imaging, vol. 6, no. 9, p. 98, Sep. 2020.

[9] S. Jadhav, S. Thorat, S. Fokane, and R. Chakre, "Classification of Parkinson's Disease Using Machine Learning Techniques," International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), vol. 2, no. 1, pp. 522–524, Aug. 2022. doi: 10.48175/IJARSCT-7012.

[10] S. Kanagaraj and V. Namitha, "Detecting Parkinson's Disease with Image Classification – Survey," International Journal of Innovative Science and Research Technology (IJISRT), vol. 6, no. 11, pp. 1138–1139, Nov. 2021.

[11] S. Sivaranjini and C. M. Sujatha, "Deep learning-based diagnosis of Parkinson’s disease using convolutional neural network," Multimedia Tools and Applications, Mar. 2019. doi: 10.1007/s11042-019-7469-8.

[12] S. Shinde, M. Prasad, S. Saboo, D. Kaushick, and S. Saini, "Predictive Markers for Parkinson’s Disease Using Deep CNN on Neuromelanin-Sensitive MRI," Scientific Reports, vol. 9, no. 1, p. 13084, Sep. 2019.

[13] S. Zhu, "Early Diagnosis of Parkinson’s Disease by Analyzing Magnetic Resonance Imaging Brain Scans and Patient Characteristics," The Harker School, San Jose, CA, 2023. [Unpublished].

[14] U. Chaudhari, A. Barbate, M. Ingle, P. Bhagat, and B. Bawankar, "Parkinson’s Diseases Prediction and Comparison of Machine Learning Algorithms," International Journal of Novel Research and Development (IJNRD), vol. 8, no. 4, Apr. 2023.

[15] Y. Huang, C. Liu, and W. Zhang, "Early Parkinson’s Diagnosis through Hand-Drawn Spiral and Wave Analysis Using Deep Learning," Information, vol. 15, no. 1, p. 37, Jan. 2024.

[16] Manikandan, S., & Kaladevi, N. (2022). Hybrid Deep Learning Model for Parkinson Disease Diagnosis using Voice Features. Materials Today: Proceedings, Elsevier.

[17] Mandal, I., & Sairam, N. (2014). New machine-learning algorithms for prediction of Parkinson’s disease. International Journal of Systems Science, 45, 647–666.

[18] Mostafa, S. A., et al. (2019). Examining multiple feature evaluation and classification methods for improving the diagnosis of Parkinson’s disease. Cognitive Systems Research, 54, 90–99.

[19] Muhammad Asad et al. (2021). Audio-Based Convolutional Neural Network for Early Detection of Parkinson’s Disease.

[20] Pooja Raundale et al. (2021). Prediction of Parkinson’s disease and severity of the disease using Machine Learning and Deep Learning algorithm. INCET 2021, IEEE.

[21] Prashanth, R., et al. (2016). Automatic classification of Parkinson’s disease from speech signals using deep learning. Journal of Medical Systems, 40, 53.