Parkinson's Disease Detection Using MachineLearning Algorithms

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Abstract—This study focuses on improving the diagnosis of Parkinson's disease by using CNN (Convolutional Neural Net- work) technology to analyze brain MRI scans. Parkinson's diseaseis a disorder that affects movement and is often hardto diagnose accurately due to similarities with other movement- related conditions. Our goal is to create a model that can tell the difference between people with Parkinson's and those without it by detecting unique patterns in MRI scans. CNNs are powerful tools for recognizing detailed patterns in images, allowing the model to pick up on subtle changes in the brain that may not be obvious through standard examination. By training this model on a wide range of MRI images, we aim for it to make consistent, reliable diagnoses, helping doctors to reach conclusions faster and more accurately. This approach could reduce the time needed for diagnosis, cut down on errors, and ultimately help patients get the right treatment sooner.

Key Words: Parkinson's Disease, Deep Learning, Convolutional Neural Network, Classification, Classifiers (SVM, DecisionTree, KNN, ANN).

I. INTRODUCTION

Parkinson's disease is a progressive neurodegenerative dis- order characterised primarily by motor disturbances in movement, coordination, and balance. It is caused by the degeneration of dopaminergic neurons of the substantia nigra, an area of the midbrain. Dopamine is involved in the control of smoothmovements, so when their levels are decreased, patients begin to exhibit different motor symptoms which make it challengingto carry out everyday activities. Early symptoms include tremors, bradykinesia-slowness of movement-muscle rigidity and postural instability. These symptoms tend to occur together with those of several other neurological conditions, making early and accurate diagnosis challenging. Standard methods of diagnosis by clinical evaluation and MRI scans fail to demonstrate major structural changes within the brain until fairly late in the course of the disease, thus leading to delayed diagnosis and treatment in most patients.

Machine learning, in the recent past, has shown promising potential in aiding early diagnosis of Parkinson's disease. Fur-thermore, CNNs are highly effective since they automatically analyze MRI scans and detect patterns or anomalies not easily noticed by the human eye. Since it is an automatic approach, the possibility of error due to man is much minimized because disease markers are always identified in different patients, hence yielding more reliable and reproducible results. With CNNs in neuroimaging, the amount of time taken to reach a diagnosis is significantly reduced, thus accelerating intervention and potentially helping in expediting treatment planning. Since Parkinson's disease impacts close to 5.8 million people worldwide, killing around 329,000 every year, early detection and intervention through CNN-driven MRI analysis is a giant leap forward for healthcare.

II. LITERATURE SURVEY

There are many studies in this literature review that utilize emergent technologies, including AI, deep learning, imageprocessing, and IoT for diagnosing and managing Parkinson's disease. Early neuroimaging and cognitive markers need tobe diagnosed urgently, as suggested by Lub Xya Hli [1].

Nalini et al. (2023) [2] improved the computer vision and IoT detection of improved scenarios in the analysis of medical images. Ruhmann et al. (2018) demonstrated the combination of image processing with AI to successfully analyze diseases [3]. Ali et al. (2022) designed neural net- works to improve the model for diagnosis [4]. Rana et al. (2022) employed SVMs, which were adopted for accurate early detection [5]. Xu et al. (2022) described deep learning techniques applied to track neural activity [6]. Naseer et al. (2021) improved strong detection by the application of modern AI techniques [7]. Rumman et al. (2018) discussed early detection using ANN with image processing [8]. Alhussein and

Muhammad analyzedvoice pathology using machine learning [9]. Pereira et al. (2016) wrote about predictive learning for Parkinson's disease [10]. Logemann et al. (1978) shared some insights about the vocal dysfunctions [11]. Zhang et al. (2019)analyzed neural activity pattern using resting-state fMRI [12]. Mucha et al. (2018) address dysgraphia in advanced stages of Parkinson's [13]. Meijer and Goraj (2014) study MRI findings for tracking disease progression [14]. Finally, Rana et al. (2022) have reviewed several machine learning algorithms for its early detection [15]. Together, the studies highlight the increasing use of technology in boosting accuracy in diagnosis and innovation for early detection and management of the disease.

III. PROPOSED SYSTEM

The system uses CNNs to analyze MRI scans to treat Parkinson's disease. Use pre-trained VGG16, VGG19, and ResNet50 models to extract features. Some pre-processing is done by resizing, normalizing, and enhancing the image. Select the model that gives the best accuracy among various models such as SVM, Decision Tree, KNN, ANN, etc. Accuracy is divided by accuracy, improvement, and F1 score.

METHODOLOGY

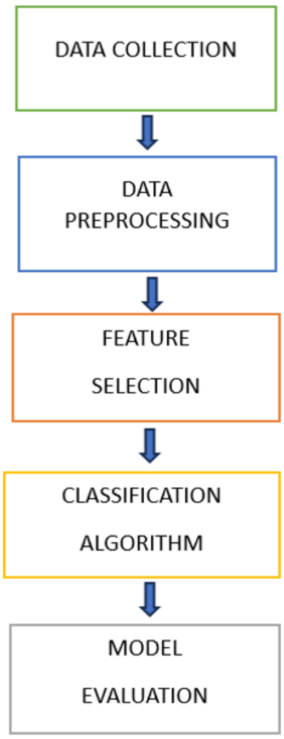

Fig. 1. proposed architecture

Fig 1 depicts the stages of evaluation of the model namely:

A. Dataset Details

The first step is to collect data including all MRI images divided into five dementia levels, each including 154 validation images, 3,601 training images, and 3 test images. It has a resolution of 640x640 pixels.

B. Data Preprocessing

The MRI images are resized to 640x640 pixels, normalized, and augmented using rotation, motion, and translation. The dataset is divided into training (80%), validation (10%), and testing (10%) sets.

C. Feature Selection

Feature extraction is performed using CNN models such as VGG16, VGG19, and ResNet50. VGG models are deeper, while ResNet uses residual learning to avoid the vanishing gradient problem. The features extracted are used for classification using various machine learning algorithms.

D. Classification Algorithms

The classification algorithms used include SVM, decision tree, KNN, and ANN. Performance is evaluated using accuracy, precision, recall, and F1-score.

IV. EXPERIMENTAL RESULTS

The experimental results obtained from applying various classification algorithms on features extracted using different deep learning models demonstrate notable performance differences. For VGG16, the accuracies achieved were as follows: SVM at 93.19%, Decision Tree at 92.86%, KNN at 96.51%, and ANN at 94.19%. In the case of VGG19, the resultsshowed a slight improvement with SVM achieving 94.85%, Decision Tree at 92.36%, KNN at 96.35%, and ANN remaining consistent at 94.19%. However, the ResNet50modelexhibited the highest overall performance, with SVM reaching 94.35%, Decision Tree at 93.19%, KNN achieving 96.68%, and ANN showing an impressive accuracy of 96.35%.These resultsindicate that ResNet50 not only maintains high accuracy across different classification algorithms but also outperforms VGG16and VGG19 in terms of KNN and ANN accuracy. This underscores the effectiveness of ResNet50 as a feature extractor, demonstrating its superior ability to learn complex patterns in the data.

VGG16:

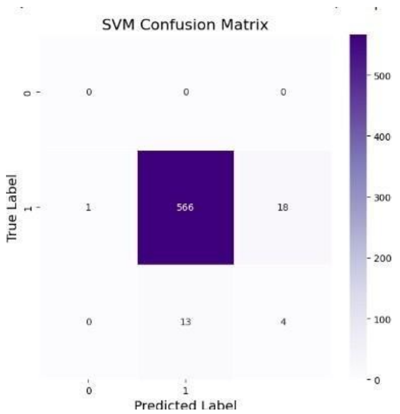

Fig. 2. SVM confusion matrix

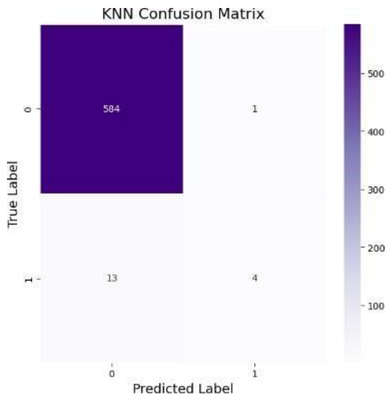

Fig. 3. KNN confusion matrix

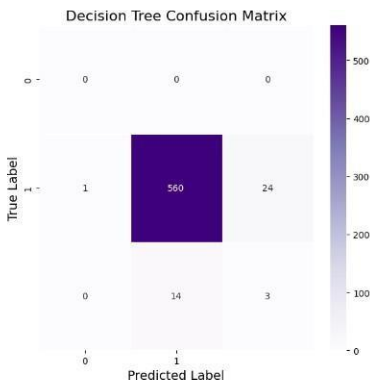

Fig. 4. Decision Tree confusion matrix

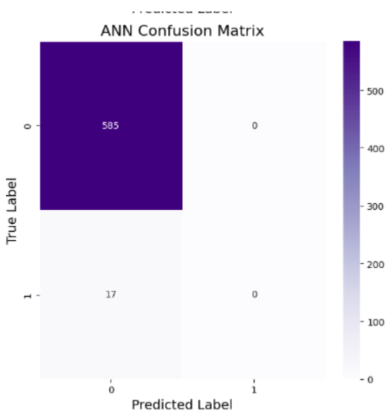

Fig. 5. ANN confusion matrix

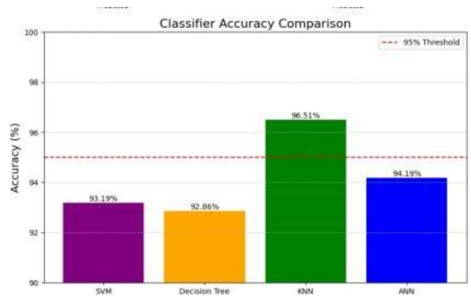

Fig. 6. Classifier Accuracy Comparison(VGG16)

From fig 2 ,from the confusion matrix it is depicted that SVMmodel predicted 566 instances correctly for class 1 (center of the matrix) and from fig 3 KNN model predicted 504instances correctly for class 0 ,from fig 4 Decision Tree model predicted 560 instances correctly for class 1,from fig 5 ANN model predicted 585 instances correctly for class 0.From fig6 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.51% by using (VGG16) as feature extraction model.

VGG19:

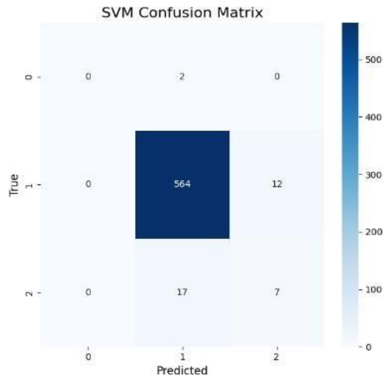

Fig. 7. SVM confusion matrix

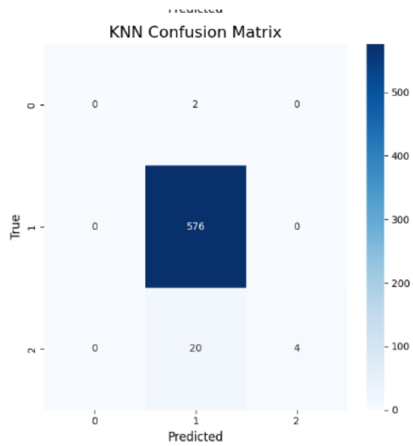

Fig. 8. KNN confusion matrix

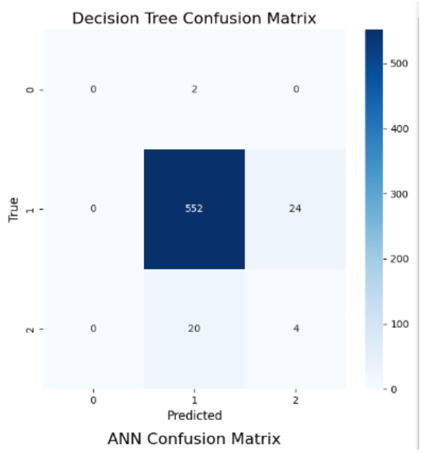

Fig. 9. Desicion Tree confusion matrix

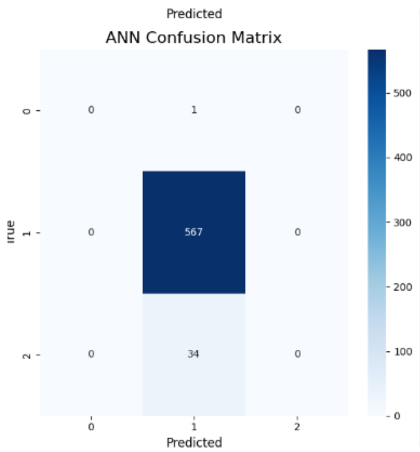

Fig. 10. ANN confusion matrix

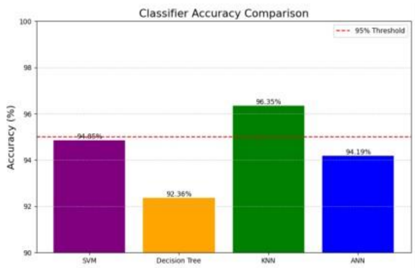

Fig. 11. Classifier Accuracy Comparison(VGG19)

From fig 7 ,from the confusion matrix it can be depicted that SVM model predicted 564 instances correctly for class 1,from fig 8 KNN model predicted 576 instances correctly for class 1,from fig 9 Decision Tree model predicted 552 instances correctly for class1, from fig 10 ANN model predicted 567 instances correctly for class 1.From fig 11 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.31% by using (VGG19) as feature extraction model.

ResNet50:

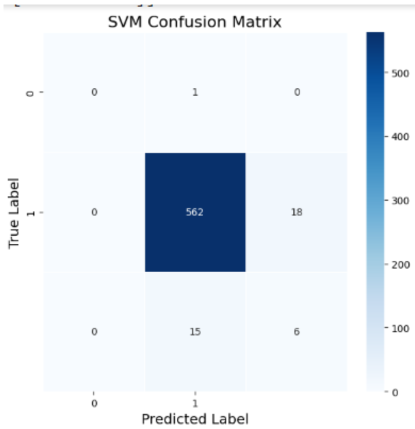

Fig. 12. SVM confusion matrix

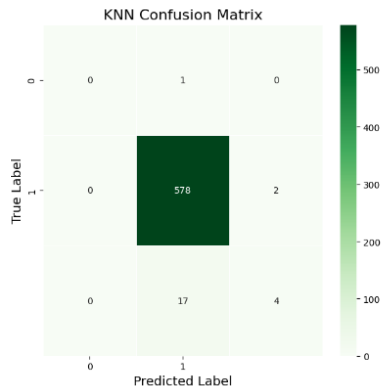

Fig. 13. KNN confusion matrix

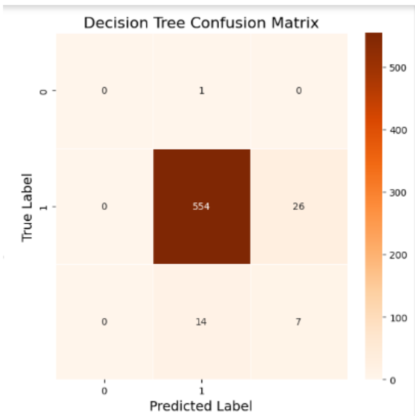

Fig. 14. Decision Tree confusion matrix

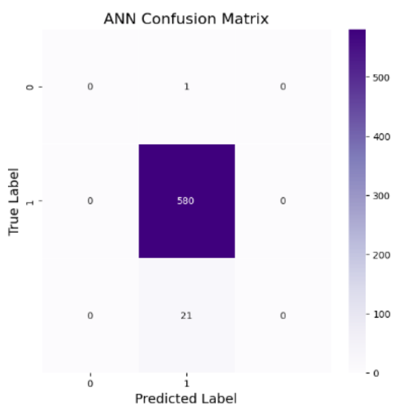

Fig. 15. ANN confusion matrix

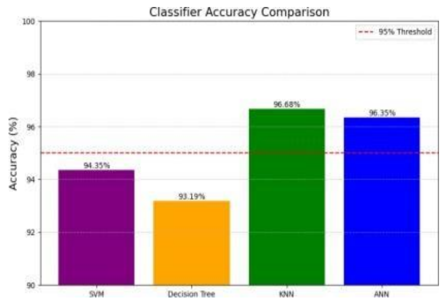

Fig. 16. Classifier Accuracy Comaprision (ResNet50)

From fig 12,from the confusion matrix it can be depicted that SVM model predicted 562 instances correctly for class 1,fig 13KNN model predicted 578 instances correctly for class1,fig 14 Decision Tree model predicted 554 instances correctly for class1,fig 15 ANN model predicted 580 instances correctly for class 1. From fig 16 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.68% by using (ResNet50)as feature extraction model.

	precision	recall	f1-score	support
1.0	0.98	0.97	0.97	580
2.0	0.32	0.36	0.34	22
accuracy			0.95	602
macro avg	0.65	0.67	0.66	602
weighted avg	0.95	0.95	0.95	602

Fig. 17. Classification Report(svm)

	precision	recall	f1-score	support
1.0	0.97	0.96	0.96	580
2.0	0.11	0.14	0.12	22
accuracy			0.93	602
macro avg	0.54	0.55	0.54	602
weighted avg	0.94	0.93	0.93	602

Fig. 18. Classification Report(Decision Tree)

	precision	recall	f1-score	support
1.0	0.97	1.00	0.98	580
2.0	0.75	0.14	0.23	22
accuracy			0.97	602
macro avg	0.86	0.57	0.61	602
weighted avg	0.96	0.97	0.96	602

Fig. 19. Classification Report(KNN)

	precision	recall	f1-score	support
1.0	0.96	1.00	0.98	580
2.0	0.00	0.00	0.00	22
accuracy			0.96	602
macro avg	0.48	0.50	0.49	602
weighted avg	0.93	0.96	0.95	602

Fig. 20. Classification Report(ANN)

From fig 17,fig 18,fig 19 and fig 20 it can depicted that the precision ,recall,f1-score of the different classifiers i.e. SVM, KNN, ANN, Decision Tree for the ResNet50 feature extractionmodel.

From fig :6,fig 11,fig 14 there can be demonstration that ResNet50 ensured high accuracies in respect to different classification algorithms and even could gain more accuracy than VGG16 and VGG19 with regard to KNN and ANN accuracy. It even reflects the effectiveness of feature extractor like ResNet50 in learning complex patterns within the data, making it an ideal choice for classifying the severity of dementia in Parkinson’s Disease. The network Ion, ResNet50 ensured to gain high accuracy toward different classification algorithms and even managed to obtain more accuracy than VGG16 and VGG19 related to KNN and ANN accuracy. It even reflects the efficiency of feature extractor like ResNet50 in learning the complexity of patterns within data, so it is an excellent choice for classifying the seriousness of dementia among Parkinson’s Disease.

V. CONCLUSION

Early diagnosis of Parkinson’s disease is crucial to achieve better results for the patients. This study found that CNN, especially ResNet50, complemented with KNN, effectively offered a candidate solution for the detection of PD from MRI images. Combining sophisticated feature extraction with robustclassification algorithms led to high-level accuracy of 96.68% for ResNet50-KNN. Future development will involve systems having real-time properties, transfer learning, and explainable AI to further increase accuracy.

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