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Advanced Deep Neural Architectures for Parkinson's Disease Prediction and Classification Systems

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ABSTRACT

Introduction: Parkinson's disease (PD) greatly decreases motor function in a progressive disease of the nervous system. Beginning accurate diagnoses establishes both on time action and more effective treatment of diseases. The traditional techniques for diagnosis depend upon individual examinations that could result in complications. The aim of this research is to examine potential of deep learning models—especially Convolutional Neural Networks (CNNs)—for PD identification and prediction integrating waveform and swirling drawing datasets as biomarkers.

Methods: AlexNet, an already-trained deep neural system renowned for its excellent feature acquiring abilities, and a custom-made CNN model were evaluated. Augmentation approaches were employed in preliminary processing to boost picture variance and endurance. Standard performance indicators including preciseness, specificity, and sensitivity steered both models' training and evaluation.

Results: AlexNet managed to retrieve convoluted spatial details and surpassed the modified CNN with preciseness by 100%. Although effectively functioning, the tailored CNN model accomplished a much less precise prediction of 93.2%. Superior accuracy and recall of AlexNet demonstrated the effectiveness in PD classifying more thoroughly.

Conclusion: This research illustrates the significance of deep learning in the diagnosis of PD through exhibiting AlexNet's superior performance. These findings affirm the prospects for machine-driven, non-intrusive effectual PD examinations. Additional data sets and blended architectures should be examined in subsequent investigations to enhance model versatility.

Keywords: *AlexNet, automated diagnosis, augmentation, customized CNN, deep learning, Parkinson's disease (PD).*

1. INTRODUCTION

PD disease is a neurodegenerative condition that is chronic and characterized by increasing motor and non-motor deficits. It affects millions of people all over the world. A timely and correct diagnosis of PD disease is essential to commence therapies that can slow the course of the disease and improve patient outcomes [1]. The conventional method of diagnosis is frequently subjective. It is based on clinical observations and neurological exams of symptoms such as tremors, bradykinesia, stiffness, and postural instability. Although these procedures are successful to a certain extent, they have substantial drawbacks, such as delayed detection and variations in interpretation among practitioners [2].

In the past, the diagnosis of PD disease was mostly based on symptom-based evaluations carried out by neurologists. The identification of motor deficiencies was also accomplished with other procedures, such as handwriting tests and assessments of motor performance [3]. Imaging methods such as SPECT and PET were utilized in conjunction with these methodologies to gain a better understanding of the loss of dopamine neurons. However, these imaging techniques are not appropriate for large-scale screening since they are not only costly but also unavailable in many places [4].

In the latter part of the 20th century, the advent of computer-aided systems presented a chance to solve a number of these difficulties. To assess patient data, statistical methods were utilized, and early computer models were utilized to forecast the evolution of the disease. On the other hand, these systems lacked the level of sophistication required to manage the complicated and high-dimensional nature of the data associated with PD [5].

By providing data-driven methodologies that could discover patterns in patient data that were beyond human vision, ML represented a significant leap in the diagnosis of PD disease. The datasets that contained characteristics collected from handwriting patterns, voice recordings, gait analysis, and clinical ratings were subjected to the application of traditional ML models such as SVM, k-NN, Random Forests, and Logistic Regression [6]. Through the process of learning from labeled data, these techniques enhanced accuracy and consistency.

Despite these developments, previous machine learning models relied primarily on human feature engineering. This meant that domain specialists were required to create and extract features from raw data. It took a lot of time, there was a possibility of bias, and it was difficult to capture the complex, non-linear correlations that were present in high-dimensional datasets [7]. Furthermore, since there was a wide range of data gathering procedures, these models frequently had difficulty generalizing across a variety of datasets.

The following is the paper's structure: Section 2 conducts a literature review on previous work on Parkinson's disease prediction and detection using machine learning models. Section 3 describes our methodology, including how we collected data, processed it, and then used a feature selection algorithm and a deep neural network architecture. Section 4 presents the experimental results and compares them to previous work. Finally, Section 5 summarizes our findings and discusses their implications.

2. LITERATURE SURVEY

Early detection of Parkinson's disease was the focus of a variety of research projects that were undertaken by several different organizations. Mohamad Alissa and his colleagues [8] revealed that they have received a diagnosis of Parkinson's disease by the utilization of CNN and exercises involving figure-copying. Through the utilization of drawing activities, the objective of these tasks was to identify variances in the motions of the patients. For the goal of predicting the likelihood of a person suffering from Parkinson's disease, the research that was carried out by Y. Zhang [9] utilized support vector machines and random forests as models of machine learning. This was done within the framework of the analysis of gait data. As a result of the findings, which were positive, it appears that these models have the potential to be utilized for the early diagnosis of the illness among the public.

An investigation into the use of DL to the prediction of the development of PD disease based on neuroimaging data was carried out by S. M. A. Asaduzzaman Sakib and colleagues [10]. In this study, the advantages of using CNNs in MRI image research were highlighted, and a technique was presented for visualizing the sickness and its following follow-up. The research that was conducted in [11] employed machine learning to include data that was gathered from wearable devices in order to construct a prediction model. This was done in order to accomplish the overall goal of the study. Their model demonstrated a high degree of accuracy when it came to the process of identifying motor symptoms, which prepared the way for the possibility of early intervention choices.

In order to accurately differentiate Parkinson's disease from other disorders, methods for feature selection and classification were studied in [12]. The focus was on methods like SVM and ANN. Similarly, to detect patterns and alterations that follow the advancement of Parkinson's illness, [13] employed wearable sensors and deep learning models, which comprised CNNs and RNNS.

An automated machine vision system was described by Nabeel Seedat and colleagues [14], which enabled the identification of movement abnormalities from hand-drawn spirals. The system utilized CNN to conduct classification between Parkinson's disease (PD), control patients, and essential tremor victims. An assessment of the RNN models for PD classification was reported by Arjun Shenoy and colleagues [15], who used drawing data in their process. Compare and contrast the recurrent network models (LSTM) and echo-state networks that were presented by the authors.

3. METHODS

For predicting and classifying PD disease utilizing biomarkers such as wave and spiral drawing datasets, the suggested technique makes use of a pipeline that is both methodical and well-structured. The process is comprised of the distinct steps that are explained below:

1.Dataset Collection

2.Data pre-processing

3. Deep Neural Architecture Model (AlexNet Model)

4.Model Training

5.Model Testing

1.Dataset Collection: Joao Paulo Folado and Adriano de Oliveira Andrade, both National Institute of Applied Technology of the Federal University of Uberlandia, were the ones that developed the dataset [16, 17].There are 204 images in the collection, and they range in size from small to large. The data set is composed of two distinct types of drawings: spiral and wave. The number of images that belong to each category is 102. The sample two distinct types of images are shown in Figure 1.

2. Data Pre-processing: To maintain the quality of the input data for the deep learning models and to improve their performance, it is vital to do data preparation in an efficient manner. The wave and spiral drawing datasets are the ones that are put through the data augmentation process for this study. While the wave and spiral drawing dataset is being used for Parkinson's disease prediction, data augmentation techniques play a significant role in improving the variability and resilience of the dataset. The purpose of these approaches is to create positional and orientation diversity. Some examples of these techniques are random rotation, flipping (horizontal/vertical), zooming, and translation. Simulating different data gathering settings may be accomplished with intensity-based augmentations, which include alterations to brightness and contrast, as well as the inclusion of Gaussian noise. The sample dataset information and corresponding number of images in class wise is shown in Figure 2.

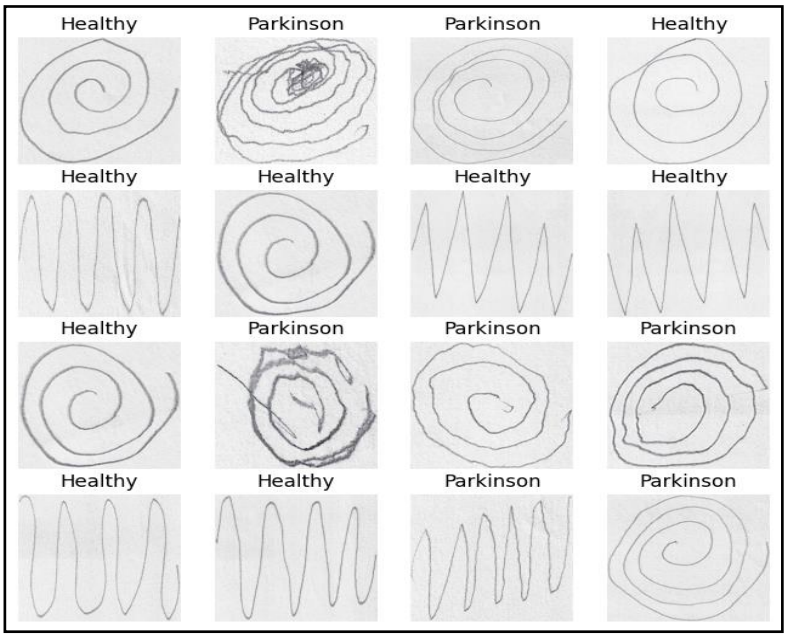


Figure 1. Sample PD disease images

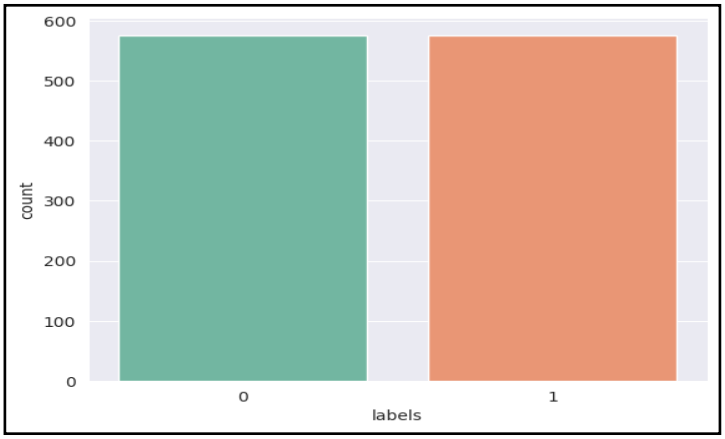


Figure 2. PD disease images count distribution in class wise

3.Deep Neural Architectures Model (Alex Net): There are 5 convolution layers, 3 pooling layers, and 3 fully connected layers making up AlexNet, which is an eight-layer convolutional neural network. During the training process, AlexNet was

trained using more than one million photos and more than one thousand categories from the ImageNet database. As input, it can accept photos with dimensions of up to 227x227x3 pixels: Specifically, the width and height of the input picture are indicated by the resolution of 227×227 with 3 channel images. A total of 96 filters, each having an 11x11 filter size and four strides, are included in the first convolution layer. Table 1 shows parameters set for the model.

Table 1. AlexNet model parameter information

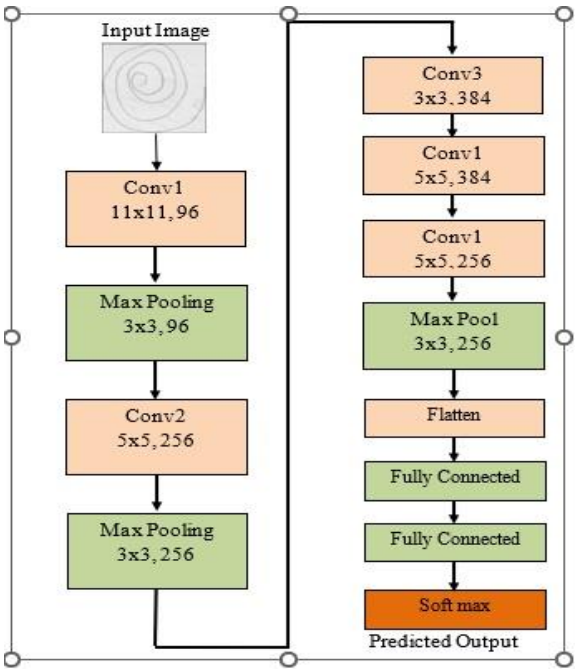
Layer	Filters	Filter Size	Stride
1	96	11 × 11	4
2	256	5 × 5	1
3	384	3 × 3	1
4	384	3 × 3	1
5	256	3 × 3	1

The 2nd layer of convolution is composed of 256 filters, each of which has a stride of one and a filter size of 5x5. There are 384 filters comprising the third convolution layer, each of which has a dimension of 3x3 and a single stride. 384 filters with a filter size of three by three and a stride of one are utilized in the 4th convolution layer. A filter size of 3x3 and a length of one stride are possessed by each of the 256 filters that are contained inside the fifth convolution layer. The information on the number of convolutions, filter size, and stride is presented in Table 1, accordingly. For the ReLU and max pooling algorithms, a pool size of 3x3 is utilized to normalize each subsequent convolutional layer. An illustration of the AlexNet system's overall design layout may be seen in Figure 3.

4.Model Training: The process of training a model to predict PD disease begins with the preparation of the dataset, which is the first stage in the process. The dataset is split into three distinct sets: the training set, the validation set, and the testing set. The goal of this is to guarantee that the distribution of classes is balanced. The process of training involves the employment of categorical cross-entropy as the loss function, the Adam optimizer with an initial learning rate of 0.001, and a learning rate scheduler that makes dynamic modifications to the rate based on the performance of the system. All these components are components of the training method. By employing regularization techniques like dropout layers and L2 weight decay, as well as early halting based on validation loss, it is possible to avoid overfitting from occurring.

5. Model Testing: The trained model is evaluated using a test dataset that has not been seen before. To ensure consistency, the test dataset has been preprocessed in the same manner as the training data. To evaluate and test the model used various evaluation metrics.

Figure 3. Architecture of Deep Neural Alex Net Model



4. EXPERIMENTAL RESULTS AND METRICS

To demonstrate the efficacy of the suggested method, several experiments are carried out, and this part contains a comprehensive comparative analysis as well as a breakdown of the findings. Using several deep learning libraries, such as Open CV, Numpy, Matplotlib, and sklearn, the experiments are carried out in Jupyter Notebook and Anaconda Prompt IDE. MRI images were used to train and test the various transfer learning models, which were trained and evaluated using Keras and TensorFlow on a corei7 processor running at 2.6GHz, a hard disk drive with 1TB of space, and 8GB of RAM.

Evaluation Metrics: Numerous metrics are utilized in order to evaluate the accuracy and dependability of the predictions made by a Parkinson's Disease prediction model in order to determine how well the model performs. In terms of accurately recognizing Parkinson's disease using wave and spiral drawing datasets, these metrics offer insights into how well the model performs in terms of its performance. The various evaluation metrics like accuracy (ACC), precision (PPV), recall (TPR) and F1-score (F1-Sc) can be shown in Equation 1-4.

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP+TN+FP+FN}} \quad (1)$$

$$PPV = \frac{TP}{TP + FP} \quad (2)$$

$$TPR = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = 2\,X\,\frac{PPV\ X\ TPR}{PPV + TPR} \quad (4)$$

Results Analysis and Discussions: The traditional CNN model and Deep Neural architecture Alex Net models have been taken into consideration and reviewed in this section. The Dropout and Adam optimizers were utilized to circumvent the issue of overfitting from occurring. As shown in Figure 4, during the training and verification process, the CNN and pre-trained deep learning model was trained for a maximum of twenty epochs in duration.

The training process for both models involved 20 epochs, with AlexNet showing faster convergence, reaching a final training loss of 0.02 and validation loss of 0.04, compared to the traditional CNN's final training loss of 0.15 and validation loss of 0.18. The suggested PD AlexNet model's sample prediction is displayed in Figure 5, which can be found here. The results highlight the superior performance of AlexNet in identifying Parkinson's disease from wave and spiral drawing datasets, attributed to its deeper architecture and pre-trained weights. As can be seen in Figure 6, the confusion matrix of the suggested PD deep neural architecture AlexNet model is displayed.

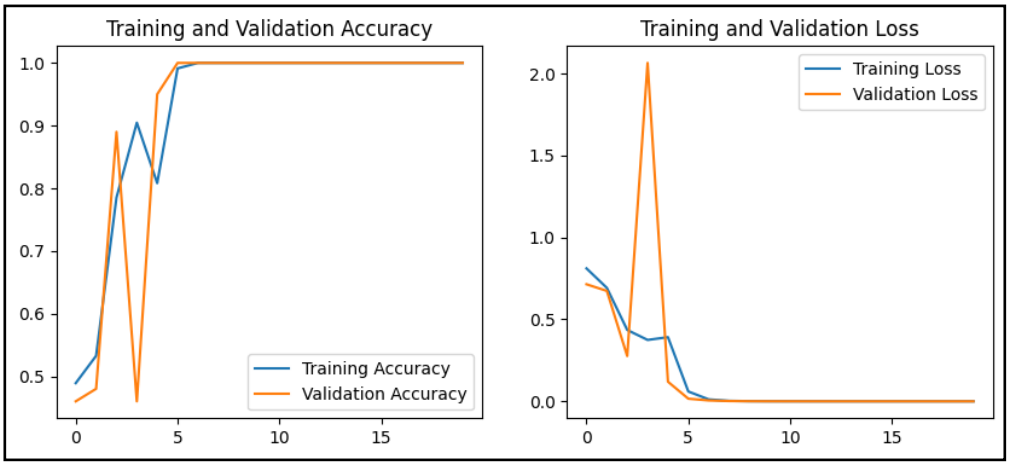


Figure 4. Training, Validation accuracy and loss of PD model

The results show that the AlexNet-based model outperformed the traditional CNN model in all evaluation metrics, with AlexNet achieving an accuracy of 100%, compared to the traditional CNN's ACC of 93.2%, PPV of 91.8%, TPR of 94.1%, and F1 of 92.9%.

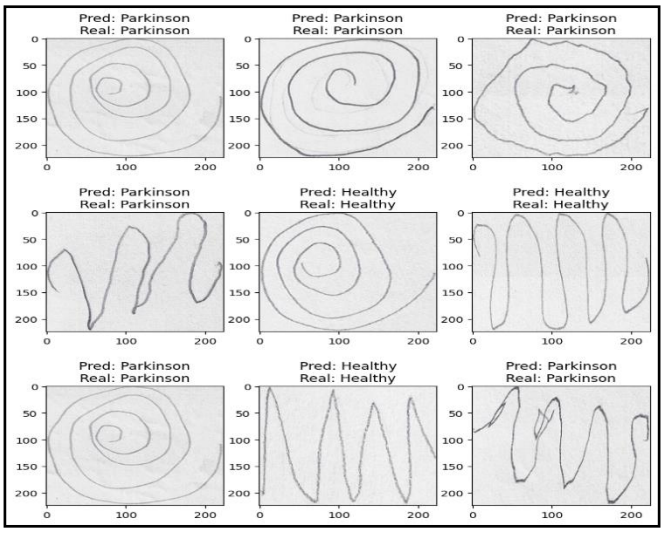


Figure. 5 Prediction of proposed PD Alex Net model

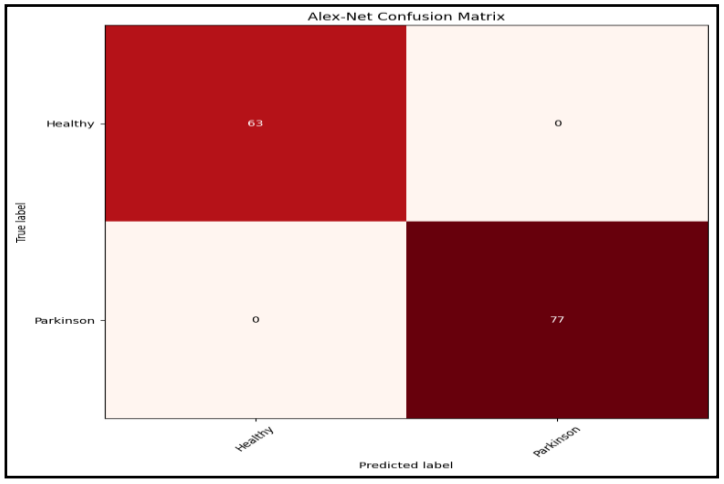
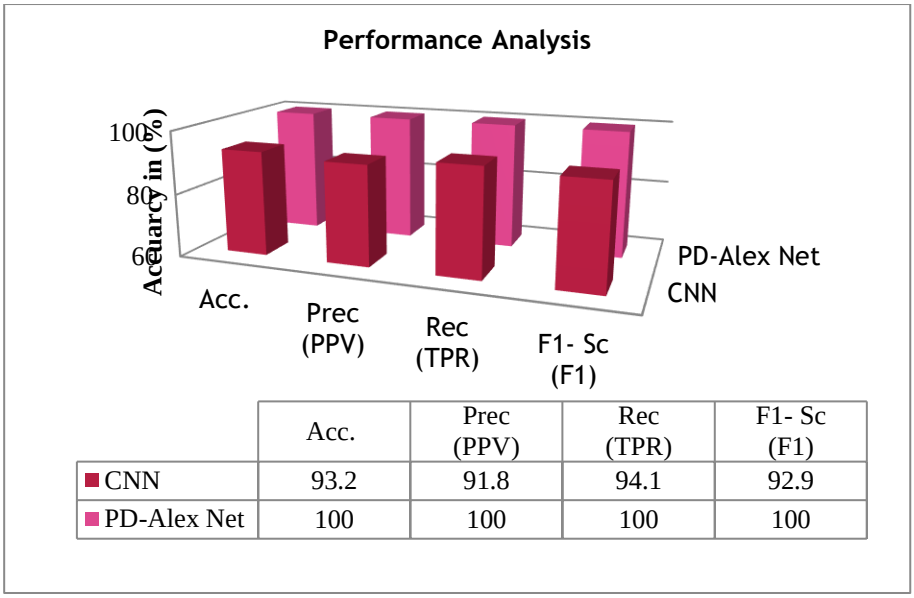


Figure 6. Confusion Matrix of proposed PD AlexNet model

Based on the results of the experiments, we can notice that a classification network that is based on deep learning is capable of extracting features from pictures, as well as performing hierarchy abstraction and categorizing the Parkinson's disease using two different datasets. When compared to other standard deep learning CNN models, the performance and classification of Alex Net models are superior. This is seen in Figure 7, which shows the results of the comparison.

A benchmark contrasting between the proposed PD-Alex Net and the traditional CNN model shown in figure 7. Four measures accuracy, precision, recall and F1-score are being evaluated. With an ideal score of 100% in every one of the measures, PD-Alex Net finished more astoundingly. CNN earned less, with 93.2% accuracy, 91.8% precision, 94.1% recall, and 92.9% F1-score. These results convey that PD-Alex Net recognizes and categorizes Parkinson's disease considerably more proficiently than other approaches. Vital for healthcare diagnosis, a desirable recall value additionally demonstrates no false negatives. The steady improvement over all the evaluations suggests the reliability and resilience of the claimed technique. Good feature collection and model design could be beneficial factors for this enhanced measures.



	Acc.	Prec (PPV)	Rec (TPR)	F1- Sc (F1)
CNN	93.2	91.8	94.1	92.9
PD-Alex Net	100	100	100	100

Figure. 7 Performance analysis of proposed PD model with existing approaches

5. CONCLUSIONS

The findings of this study offer conclusive evidence that Convolutional Neural Networks (CNNs), and more specifically the AlexNet architecture, are capable of accurately diagnosing and categorizing Parkinson's Disease (PD) by utilizing wave and spiral drawing records as biomarkers. The quality of the features collected from the pictures was significantly improved by the utilization of CNN-based architectures for automated feature extraction and classification. This resulted in an increase in the predictability of the model. AlexNet outperformed the custom CNN, which obtained an accuracy of 93.2%, according to the comparison between the two. AlexNet achieved a stunning accuracy of 100%, which was a significant improvement over the custom CNN's performance. The results of this study highlight the effectiveness of deep learning models, particularly pre-trained architectures such as AlexNet, in identifying intricate spatial patterns that are linked with Parkinson's disease (PD). This presents a viable strategy for precise and timely diagnosis.

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