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Non-invasive Detection of Parkinson's Disease Using Deep Learning

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Abstract: Being a near end to a confident life, there is no simple test to diagnose stages of patients with Parkinson's disease (PD) for a patient. In order to estimate whether the disease is in control and to check if medications are regulated, the stage of the disease must be able to be determined at each point. Clinical techniques like the specific single-photon emission computerized tomography (SPECT) scan called a dopamine transporter (DAT) scan is expensive to perform regularly and may limit the patient from getting regular progress of his body. The proposed approach is a lightweight computer vision method to simplify the detection of PD from spirals drawn by the patients. The customized architecture of convolutional neural network (CNN) and the histogram of oriented gradients (HoG) based feature extraction. This can progressively aid early detection of the disease provisioning to improve the future quality of life despite the threatening symptoms by ensuring that the right medication dosages are administered in time. The proposed lightweight model can be readily deployed on embedded and hand-held devices and can be made available to patients for a quick self-examination.

Index Terms: Parkinson's disease, Convolutional Neural Network, specific single-photon emission computerized tomography, dopamine transporter, histogram of oriented gradients

1. Introduction

Parkinson's disease (PD) is one of the most occurring diseases amongst elderly of late. PD has reached statistics of more than a million cases in India alone. Availability of doctor's expertise may not always be feasible in remote areas. Studies have also shown that more than a 2000 USD annually spent in the diagnosis and treatment of PD.

The landscape of the medical industry currently is such that many lab tests and rigorous invasive processes replaced by easier and painless techniques. PD being a dreaded brain disorder can result in a huge amount of pain and trauma if one has to perform invasive testing to understand the stages of the disease. Popular brain diseases like Alzheimer's and Parkinson's being irrecoverable, are in the interest of researchers for exploring early detection techniques. Alzheimer's can also be detected using drawing based tests such as the clock drawing test, however, not a lot of detail can be extracted from the CDTs in Alzheimer's using the conventional image processing approach. Neural networks however face constraints of requiring heavy volumes of data and huge computational power. While the latter can be available at central facilities, data in massive volumes cannot be collected for patients with neural disorders. This is due to regulatory reasons and due to the fact that such patients may not be willing to perform the test in many cases. This makes it important to have technology that is less dependent on data [1, 2, 3, 4, 5].

Sparse data can be a challenge to process for most classification tasks. The trade-off between the lack of data and the precision of classification are achieved by using a more robust pre-processing pipeline. Image processing approaches like those that Histogram of Oriented Gradients extensively used for feature extraction. This extractor when applied with spiral drawings dataset produces marvelous results in terms of extracting those features that are important to detect the pen pressure and spot the variations in the different stages of PD.

The coupling action of the lightweight HOG approach with the Support Vector Machine (SVM) achieved after multiple iterations of fine-tuning the SVM detector to ensure the features chosen are relevant to the neural network before it enters the classification phase. SVM focuses on the cross section size of the objects in the frame. In the case under consideration, SVM is going to feature the thin circles drawn by the patient [6, 7, 8].

The sparsity problem can be resolved by the choice of lightweight DNN architecture for the classification task. The task at hand having images having major similarity can be challenging to use a sparse network. However, a non-conventional parameter tuning to set the middle layer sizes is developed after multiple iterations. With the recommended model, the classifier can distinctly and quickly perform classification between the various stages of PD.

Lastly, the model being very easily portable it can be employed in any kind of device such as a smartphone or tablet PC with a camera. This would make the detection process easier for the patient and there would be sufficient understanding of the problem to correctly diagnose in time with the right set of medications. The model would be optimized with NVIDIA tensor to be able to run without delay in a mobile phone or a constrained processor.

The significant contributions under this work can be summarized as follows.

- Non-invasive approach to detect PD as against existing techniques that majorly revolve around expensive CT and MRI scans
- Enhanced pipeline involving deep NN to classify PD individuals from the control. Novel feature set and pre-processing pipeline produces classification that is more robust.
- Lightweight Model (in 100s of KBs) that can easily deployed in low end embedded hardware for mobile diagnosis
- Comparison of major scores of performance such as specificity and sensitivity of both the clinical and the proposed technique
- Deployment of proposed systems in advanced devices such as NVidia Jetson Nano for portable medical edge computing based diagnostic use cases

The paper is organized in the below mentioned method. Section 2 involves Literature survey and understanding along with some justification to the usage of the proposed techniques. Section 3 describes the details of the methodology that is adopted. Section 4 involves the enumeration of results achieved through the experiments. Section 5 enlightens the various inferences made from the results. Section 6 concludes the paper with the possible future extensions of this proposal.

2. Literature Review

Extensive study has been conducted to understand the impact of wave and spiral patterns on the stages of PD and they have resulted in the conclusion that this is the most effective way to get a noninvasive diagnostic of the disease. Availability of doctor's expertise may not always be feasible in remote areas. Studies have also shown that more than a 2000 USD annually is spent in the diagnosis and treatment of PD. With the evolution of technology it becomes a pressing need to reduce the cost involved and the travel complexity in such cases when the disease itself can result in a traumatic experience to the patients and their caretakers.

Zham et al. [9] proposes the employment of Composite Index of Speed and Pen-pressure (CISP), a novel approach to determine the stages of PD. Multiple statistical tests are testimony to the fact that the correlation between the pen pressure and the speed of writing with the stages of Parkinson disease is very high. The non-parametric k-sample Kruskal–Wallis test demonstrated that PD stage1 and PD stage 3 had absolutely different scores. While penmanship of an individual is affected by various factors, for example, language capability and education, drawing of a shape, for example, the winding has been seen as non-intrusive and autonomous measure [9].

Early detection of Parkinson's disease (PD) was demonstrated using a more rigorous approach using a scan imaging processing technique. Dopaminergic images such as Single Photon Emission Tomography (SPECT) using 123 I-Isoflurane are found to detect PD at an early stage. These human understood images pose an area to automate the detection of the same. Human errors could drive in additional inconsistency in detection. In order to enhance the understanding of the developments of PD, a deep learning based model was evolved to detect PD using image processing and artificial neural networks (ANN). The model used 200 SPECT images, few from the control class and few from, selected from Parkinson's Progression Marker's Initiative (PPMI) database and processed to find the area of caudate and putamen which was the specific area of focus in the image for this particular model. The zone estimations of ROI were then nourished to the ANN which is speculated to impersonate the example acknowledgment of a human spectator. The straightforward yet quick ANN assembled, could group subjects with and without PD with an accuracy of 94%, a sensitivity of 100% and a specificity of 88%. Subsequently it very well may be induced that the proposed framework can possibly be a compelling method to help the clinicians in the exact conclusion of PD [10].

The assessment of voice, touch and memory in the design of an effective PD detection platform can be analyzed in another paper. Deep learning methods were distributed to obtain more improvements in the predictive performance over solid foundations (area less than the effective element of the finder = 0.85) from a larger database of over 1800 users. Models indicate the identification of logical features in a given dataset. Their results also suggest that smartphone data collected over an extended period of time in your future can be used as a digital biomarker in the diagnosis of Parkinson's disease [11].

An android app was developed to detect PD. The paper covered the analysis of whirls, spiral and other diagnostic criteria for PD as the most debilitating problems in the nervous system in the middle-aged to the elderly. The Octagon tracking function is introduced along with the standard Archimedean function of the wind because the shape tracking function with clear consecutive features can increase the likelihood of detecting tremors and other key features of PD [12].

Ren et al. [13] shows that a compute mask can be used to lower the computational requirement to a high-resolution network used for various processing purposes. The CNN sparse variability function has previous insights from previous publications for small tasks and has shown no compromise in terms of material accuracy. However performance has been measured in theoretical FLOPs without realizing the effective speed as compared to optimizing the optimum performance of the rigidity. In this work, we derive the sparsity formulation of compaction masks that have been generated and analyzed by a tiling-based sparse convolution algorithm. A network built from the inspiration of such a design can produce many expected results of a complete understanding of the work done without the need for heavy data and computational power to do the training. Previous art reports the essential acceleration of wall-ups as opposed to rigorous detection without any apparent reduction in accuracy [13].

Another author has proposed a sequencing sequence (S2S) framework that incorporates the encoder-decoder LSTM mode configuration. The proposed encoding module has a Convolutional LSTM network, which reads an offline character image as input and then encodes the feature in hidden authentication. The embedded output is passed to the decoder LSTM and we get the corresponding points for all decoder LSTM step times. Although sequence modeling is a popular paradigm in various computer simulations and language interpretation, the main contribution of their work lies in building the final network of the nation's 10 most popular image analysis problems. Tamil, Telugu and Devanagari characters for the LIPI Toolkit are used in our experiments. This method however as it is extremely expensive it is difficult to train it with low computation devices and use it on embedded devices such as smartphones. This method provides some insight into how it may be deploying model hyper parameters and image input pipelines that can be used to resize images before sending them to a partition function [14, 15, 16].

In a high accuracy study the important time count data from 103 studies (including 32 with severe PD severity and other non-PD residues) were considered extremely complex and difficult to capture. However there was a finding of PD symptoms at a more accurate rate. The images could be used and the use of a few other touch sensors may be inexpensive and readily available to all patients. Subsequently a combination of machine learning models was used for the classification task. When applied to two different participant groups, this method was able to successfully discriminate between the first PD subjects and control with a sensitivity of 96%, a specificity of 97% and an AUC of 0.98 [17].

3. Methodologies

The classification can be attempted using much computationally lighter algorithms such as clustering and random forest. Hence, the methodology proposed uses the Histogram of Oriented Gradients Based approach to localize the features in the drawings. Once the features are extracted, a sparse neural network will be used for classification. The results can be compared with the use of random forests for classification and the different accuracy scores can be analyzed.

Since obtaining patients with different stages of PD in a span of a single locality is challenging, the dataset is relatively limited in size to train a DNN with a heavy non-linear mapping architecture. Another approach that could enhance the generalization of the model being trained on the processed image data is the SBNet based architecture. Being a sparse architecture it sets inspiration to develop similar structural layers for the development of a custom model that can learn from less data.

A. Preprocessing Pipeline

The images from the NIATS dataset are 200x200, RGB valued images. These images are first converted into grayscale. Now, a combination of two thresholding schemes is applied to the grayscale image. A binary thresholded image is first obtained with a certain fixed value. Now the resultant binary thresholded pixel of the entire image is used in an operation with the grayscale image version that is thresholded using the Otsu Banalization and finding the mean of the obtained values [18, 19]. The middle value of the binary histogram is estimated so that the Otsu algorithm finds the optimum threshold value for partitioning the pixels so that the drawings/ darker lines are differentiable from the whitespace background of the paper on which the samples are taken.

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t) \tag{1}$$

$$q_1(t) = \sum_{i=1}^{t} P(i) \tag{2}$$

$$q_2(t) = \sum_{i=t+1}^{I} P(i) \tag{3}$$

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \tag{4}$$

$$\mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)} \tag{5}$$

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_2(t)} \tag{6}$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)} \tag{7}$$

Equation (1) shows the weighted in-cases variance that the Otsu algorithm reduces. The value between two peaks of the binary image is discovered by the algorithm and is denoted as the optimum value of 't'. The algorithm iteratively runs over the histogram's peaks (P (i)) in order to be able to find the weighted variance and optimize the same. Equations (2-7) show how the parameters in (1) are computed.

This can be seen in the HoG phase of the processing in the block diagram as in Fig. 1.

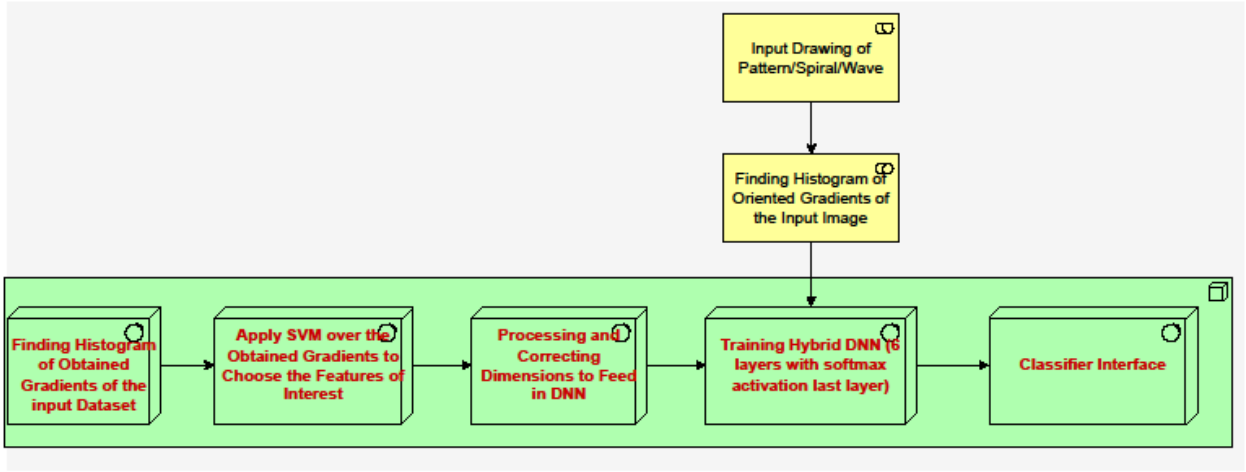

Fig.1. Block diagram of proposed methodology

B. Deep Learning Model Architecture

The architecture proposed is a deep CNN inspired by the sequential model [20]. The layers are serially fed one after the other. The model has 3 layers as inspired by [21]. This architecture is alternated by max-pooling operation after each convolution layer. The next to all connected convolution layers is a flattening layer to reduce the matrix of convolutional to a vector. The vector is now passed through a softmax output activated layer to return the output class of Parkinson's positive or negative [21]. However in contrast to that achieved in literature this is achieved using direct photographic image of the spiral drawing in contrast to the motion capture using accelerometer sensors. Use of such sensor data can be subject to availability and the accuracy numbers can be sensor specific. However, the photographic method used here is made robust to the lens or sensor of the mobile phone camera.

Pseudo Code: Pseudo Code of pipeline for sketch classification
Input: The raw images of spiral or wave drawn by the patient to be tested
Output: Classification of the image as that from PD positive or negative individual
Start
1.Convert input image to grayscale
2.Apply binary thresholding to extract the spiral/ wave pattern
3.Find Histogram of Oriented Gradients (HoG)
4.Pass these as inputs to a trained NN
4a. Load model file for NN
4b. Set the number of epochs and loss function
5.At the output of the NN perform a softmax to convert the outputs to probability- p
6.If p>0.5 then classify as PD positive or Else PD negative
End

4. Experimental Results

Here, we discuss the various parameters that strengthen our understanding of the performance of the proposed model.

A. Dataset

The dataset is of spiral and wave shaped drawings done by the subjects who were with different stages of PD. There are also images from the control subjects that were PD negative [22, 23]. Observing the sparsity of data, intuitive highly deep neural networks (DNN) based architectures fail to be the first choice. Dataset from Adriano de Oliveira Andrade, Joao Paulo Folado of the NIATS from Federal University of Uberlândia was also used for testing the algorithm.

B. Performance Metrics

AUC [24], accuracy, sensitivity and specificity [25, 26] were the chosen performance metrics for analyzing the results of the algorithms interpretation.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{9}$$

$$Specificity = \frac{TN}{TN+FP} \tag{10}$$

TP denotes True Positive, FP denotes False Positive, TN denotes true negative and FN denotes False negatives. In our case it is dangerous to have False Positives as it can misclassify a person without PD as positive resulting in a failure at the start of a disease diagnosis.

C. Computational Results

The graphs of learning can be shown below. The model shows a high AUC score of over 80% for the test set and over 90% for the training set with the limited hardware resources. If training was done for longer hours in servers like DGX-1 AUC can be expected to hit 90% from the rate of growth of AUC. The below Fig 4 and Fig 5 indicate the results of prediction of the model. The AUC shows the probability of a randomly selected diseased (Parkinson positive) individual being classified as more likely to be Parkinson positive than a randomly chosen non diseased subject. Our model shows an AUC over 0.85 shows a strong case of predicting the diseased and the non-diseased classes correctly.

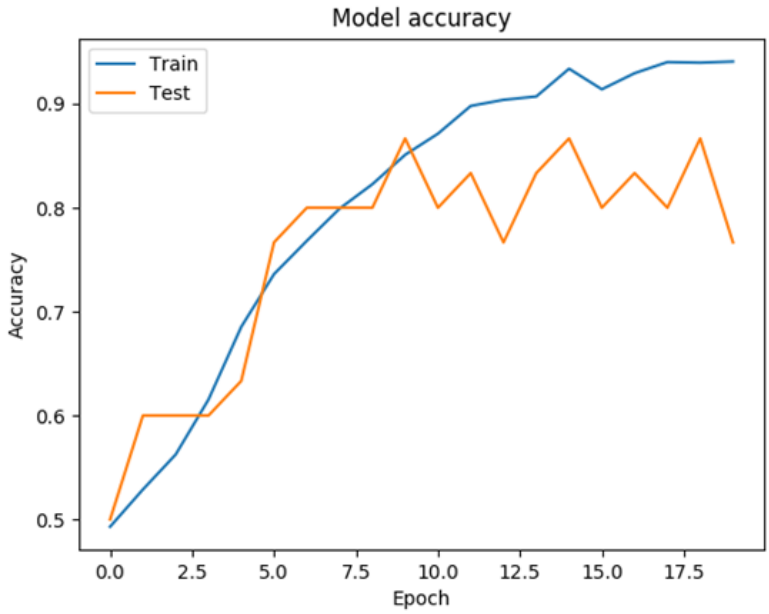

Fig. 2. The accuracy curve of the model shows that it is nearly 1 for training dataset. The validation accuracy shown by the orange curve is over 90% although training was stopped and the model was check pointed only at a later epoch (nearly 60 epochs) when the accuracy stabilized and was 90% for the validation set of spirals and whorls.

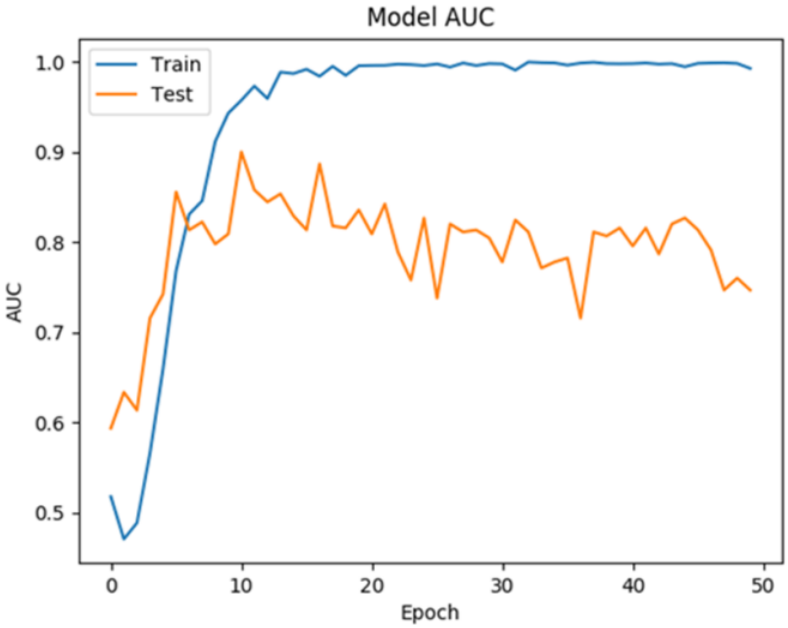

Fig. 3. The AUC of the model shows that the increasing model convergence is obtained immediately after the tenth epoch for the training set, while the convergence is different for the unseen validation set data. The validation AUC can be averaged

Fig. 4. Based on model predictions some of the test set outcomes is as shown. The test set has good variation of both positive and negative cases. The images here are classified here correctly. Due to more hand trembling in the affected patient's sketch it is rightly classified as 'Affected' and the other image is classified as a smooth and 'Healthy' individual due to fewer trembles in the handwriting.

Table 1. The table shows clearly that there is a clear-cut performance improvisation with improved sensitivity and specificity over conventional algorithms and over the clinical techniques.

	Clinical Method	Combining three vital signs (TCS)	Proposed approach using DL based method
Accuracy	73.8%	85%	94%
Sensitivity	88%	49%	80%
Specificity	68%	98%	92%

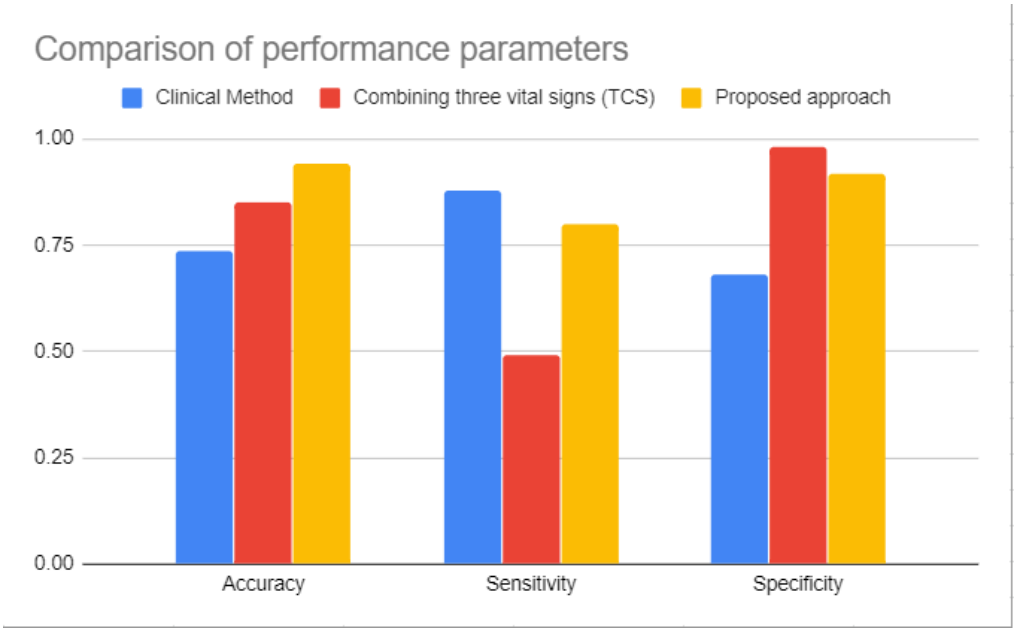

Fig. 5. Comparative study of performance metrics

5. Discussion

PD is a complicated neurodegenerative illness that is difficult to diagnose and grade for physicians and specialists. Rather than being subjective and prone to human error, observation of motor system anomalies remains the current gold standard for clinical diagnosis. The method developed clearly outperforms existing methodologies for speedy and mobile detection of a serious disease. During training there were times when high sensitivity up to 100% was achieved but at the compromise of the other score i.e., specificity. The significance of the sensitivity can be understood from the fact that the proposed model predicts all the healthy patients' classes correctly is more pronounced as compared to other approaches (from Fig. 5).

To limit the impact of this degenerative disorder and ensure that affected individuals may stay self-sufficient for as long as feasible, PD requires early diagnosis and care. However, because of the imprecise nature of clinical diagnoses and a global shortage of neurologists with expertise in PD diagnosis, PD is frequently misdiagnosed and poorly managed. The accuracy of the proposed model is competitive against other approaches and at a level that is likely to be clinically acceptable. It produces scope for improvement to use more complex data representations that encode more information by implementing transfer learning and augmentation techniques.

6. Conclusion and Future Direction

The developed algorithm along with the classifier performs well to detect the stages of PD. The DNN architecture can be deployed on any hand-held device with a simple resolution camera. Any user will be able to use the classifier for identifying the stage of PD. The results along with the confidence scores can be easily shared with clinicians for remote and early diagnosis of PD. Many symptoms based approaches rely on the availability and reliability of the data collected. This is also in contrast to some domain specific data processing and inference. With availability of higher compute the algorithm can be evolved using more data collected from organizations like National Institute of Mental Health and Neuroscience. Although many scan images based diagnosis are more available in such institutions, it is possible to perform experiments and collect live data with subjects after proper consent has been taken. Further

developments can be made to deploy the model using tensor optimization that easily runs on handheld devices and even modern cameras as on-chip software without requiring much add-on in terms of firmware level optimization. The developed non-invasive detection methodology of Parkinson's disease using deep learning approach provided improved performance with accuracy of 94%, sensitivity of 80%, and specificity of 92%. In conclusion, the realization of deep learning-assisted PD diagnosis has great promise for a more systematic clinical decision-making system; the adaptation of novel biomarkers may make PD diagnosis more accessible at an earlier stage. As a result, deep learning algorithms have the potential to give doctors more tools for screening, detecting, and diagnosing Parkinson's disease.

We intend to study the use of federated learning in future research. Federated learning can reduce numerous systemic privacy problems without exporting existing medical data sets. Federated learning is a technique for training machine learning algorithms across several edge devices without exchanging training data. Federated learning presents a new learning paradigm in which statistical algorithms are trained at the network's edge.

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