Automated Parkinson's Disease Diagnosis System Using Transfer Learning Techniques

Rohit Lamba, Tarun Gulati, and Anurag Jain

Abstract Parkinson's disease is a neurodegenerative disorder that develops in an individual when the required amount of dopamine is not produced by respective neurons. The most common symptoms of this disease are tremors or shaking in hand/arms, changes in handwriting, muscle stiffness, slowness during walking, and change in speech. It is an incurable disease, but managing its symptoms can delay its progression, which is possible only if it is diagnosed at an early stage. Prior research work had proved that variation in handwriting can be considered as a quantitative marker for Parkinson's disease diagnosis. The authors present an automated Parkinson's diagnosis system using transfer learning techniques. The performance of the presented system is analyzed by using Parkinson's spiral drawing dataset. Four transfer learning architectures ResNet 34, DensNet 121, VGG 16, and AlexNet are used to classify spiral images of Parkinson's patients and healthy individuals. The performance of these architectures was examined in terms of accuracy, sensitivity, specificity, and ROC-AUC. After fine-tuning, it was noted that the performance of all architectures improved and the AlexNet architecture outperformed with 93.33% accuracy and 0.96 AUC.

Keywords Parkinson's disease · Spiral images · Transfer learning · AlexNet · VGG16 · ResNet34 · DenseNet121

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1   Introduction

Parkinson's disease (PD) is a neurodegenerative disorder that badly affects the patient's life and usually develops after the age of 60. The core cause of the disease is a deficiency of dopamine, a brain chemical produced by neurons. When these dopamine-producing neurons start dying, results in less dopamine production and starts of Parkinson's disease [1]. The cause of these neurons dying is still to be seen. PD is incurable, so early diagnosis is the only way to improve the patient's life. Symptoms of the disease can be restrained by using a balanced diet, proper medication, and regular exercise [2]. Medications such as levodopa are used for PD treatment, as these medications aggravate left dopamine-producing neurons to produce more dopamine [3].

The symptoms of PD are divided into two types, motor, and non-motor symptoms. The slowness, tremor, instability in posture, and rigidity are some of the motor symptoms [4]. Sleep problems, depression, constipation, and anxiety are some of the non-motor symptoms. Symptoms developed in PD patients vary from patient to patient. Symptoms are mild and sometimes not noticeable at the starting of the disease, but the symptoms go severe as the disease progresses. The life of PD patients is badly affected by this disease, in some of the cases patient is not easily able to do some of the daily need works like writing or typing, eating food, walking up from the bed and washing dishes, etc. [5].

Neurologists and movement order specialists can diagnose this disease by doing an in-depth review of the patient's medical history and performing some radiological scans, for which patients have to visit the doctors repeatedly [6, 7]. As this disease mostly develops in the later stage of life around the age of 60, visiting hospitals is not easy for PD patients, so there is a scope of developing a tool for PD diagnosis which can help the health care professionals during PD diagnosis. This is the major motivation behind this research work because, in developing countries like India, health care professionals and services are limitedly available [8, 9]. Recently for disease diagnosis, deep learning techniques are widely used because of the promising results provided through data augmentation and transfer learning techniques [10, 11].

The researchers had proposed various Parkinson's detection tools by applying and utilizing different data science techniques. They have used handwritten drawings [6], speech signals [12], freezing of gait (FoG) [13], MRI images [14], SPECT images, EEG Signals [15], and EMG signals [16]. They have applied various data science techniques to the above-said numerous signals. A tremor on one side of the arm or body is one of the earliest symptoms of PD, which adversely affects the patient's handwriting or typing ability.

Parkinson's diagnosis using a handwritten drawing is been taken as an objective of this research work. To formulate the above-said objective, authors have applied transfer learning techniques to classify the spiral images of PD patients and healthy individuals. The Parkinson's spiral drawing dataset used in this work has been taken from the Kaggle repository. The substantial contributions of this research work are:

1. Initially, the authors present an automated Parkinson's disease diagnosis system using spiral drawn by PD patients and healthy individuals.
2. Furthermore, the results of four transfer learning architectures namely ResNet34, DenseNet121, VGG16, and AlexNet were compared in terms of accuracy, sensitivity, specificity, and ROC-AUC.
3. Finally, the authors have achieved an accuracy of 93.33% and an AUC of 0.96 by fine-tuning AlexNet model.

The remaining sections of this paper are organized as follows: the earlier research work is presented in Sect. 2 followed by materials and methods in Sect. 3. The results are outlined and discussed in Sect. 4. The conclusion and future scope are presented in Sect. 5.

2 Related Works

Researchers have recently used different techniques and methods for Parkinson's diagnosis using handwritten drawings. Some of the recent research work is related to automating Parkinson's diagnosis is summarized here.

Pereira et al. [17] proposed an automatic Parkinson diagnosis system and made HandPD dataset publicly available. The dataset was composed using a smartpen by Sketching Spiral and Menders by Parkinson's patients and healthy controls. Images were generated from the data collected by the sensors of the smartpen. Three transfer learning architectures such as ImageNet, LeNet, and CIFAR-10 were employed for image classification. Experiments were done by dividing the dataset into 75:25 and 50:50 train and test ratios. Results show that the CIFAR-10 gives the best classification accuracy. Pereira et al. [18] proposed CNN-based architecture to learn features derived from handwritten dynamics. The authors also made the NewHnadPD dataset publicly available. Images generated from the time-series signals collected by smartpen sensors were fed into the CNN networks. Six CNN networks each were employed for the various exams and finally, majority voting was used. Two CNN architectures namely CIFAR-10 and ImageNet were also employed. Khatamino et al. [19] proposed a CNN-based method for Parkinson's diagnosis in which the features were learned from handwritten drawing samples drawn by Parkinson's patients. The authors also introduced a new dynamic spiral test as well as a static spiral test. The data was collected from 57 PD patients and 15 healthy controls. The data was collected in two ways first, the spirals images were collected and in the second five features X, Y, Z, Pressure, and grip angle were extracted. Results suggested that the dynamic test is more discriminative than the static test. The dataset is divided into 75:25 train and test ratios and the authors achieve an accuracy of 88%.

Moetesum et al. [20] presented a study of how visual attributes can be used from handwriting datasets for the diagnosis of PD. The PaHaW dataset was used in this study which does not contain any image. Eight different handwriting tasks were performed by individuals during the data collection process. Images were generated

for every task from time-series signals by plotting x, y coordinates. Features from generated images were extracted and grouped into a combined feature vector by CNN architecture pre-trained with AlexNet. These combined feature vectors were fed into eight SVM classifiers one for each task and by majority voting and classification between healthy and Parkinson's patients was done. The results show an accuracy of 83% by ten-fold cross-validation method. Diaz et al. [21] presented how handwritten task images constructed from time-series signals of PaHaW dataset could be utilized to detect PD. 3-layer CNN architecture was used to classify the images generated from the eight different handwritten tasks. Transfer learning was also employed for performance enhancement and finally, majority voting was done at the classification stage. The authors achieved an accuracy of 86.67%. Razzak et al. [22] have analyzed different drawing tasks for Parkinson's diagnosis using deep learning techniques. PaHaW, HandPD, New HandPD, and Parkinson's drawing datasets were used to find the best drawing task that contributed more to classifying the drawing drawn by Parkinson's patients and healthy individuals. Four transfer learning architectures VGGNet, AlexNet, ResNet, and GoogleNet were employed for image classification. Experiments were performed by combining images of different datasets. The highest 96.08% accuracy was achieved by VGG16 architecture by combining the images of Parkinson's drawing, New HandPD, and HandPD datasets. Naseer et al. [23] proposed a CNN-based Parkinson's detection system using handwritten images. The study used the PaHaW dataset in which samples were collected from 75 subjects by performing eight different tasks. AlexNet, ImageNet, MNIST transfer learning techniques were employed on the dataset. The results were improved by data augmentation and fine-tuning techniques. Accuracy, precision, sensitivity, and specificity were the performance matrices used. The authors achieved 98.28% accuracy on spiral images using a trained fine-tuned network. Shaban, M. et al. [24] have proposed a PD diagnosis approach based on deep learning techniques. This study uses spiral and wave handwriting datasets downloaded from the Kaggle repository. The dataset consists of 102 wave and spiral images. The CNN fine-tuned VGG-19 architecture is used for classifying the images. Images were resized and augmented because the dataset is small in size. The proposed model achieved 89% and 88% accuracy for spiral and wave datasets respectively.

Chakraborty et al. [25] proposed a convolutional neural network approach to analyze the spiral and wave drawing patterns to detect Parkinson's disease. Dataset images were first resized and then contrast enhancement was performed using histogram equalization. Because the dataset consists of 102 spiral and wave images, hence data augmentation was applied to generate synthetic samples. Two classifiers logistic regression and random forest were used to form a Meta classifier. The proposed system achieved 93.3% accuracy with fivefold cross-validation technique. Kamran et al. [26] presented a Parkinson's diagnosis system using handwriting samples of PD patients. Images from various datasets HnadPD, NewHandPD, PaHaW, and Parkinson's spiral and wave were used in this study. Data augmentation techniques like threshold, flipping, contrast, illumination, and flipping were applied on datasets images. AlexNet, VGG16, GoogleNet, ResNet50, VGG19, and Resnet101 transfer learning techniques were used in this study.

3 Materials and Methods

3.1 Parkinson's Drawing Dataset

The Parkinson's drawing dataset used in this study is publicly available at Kaggle repository [27]. The dataset was collected by drawing spirals and waves from Parkinson's patients and healthy controls. Only spiral images are used in this study because most of the researchers have used spiral images for the diagnosis of this disease. Training and testing were two subsets in which the spiral image dataset was already segmented. The training subset and the test subset constitute 72 and 30 spiral images, respectively. Half of the images in both sub-categories are from patients with PD while the rest are from healthy individuals. The sample of images drawn by PD patients and healthy individuals is shown in Fig. 1.
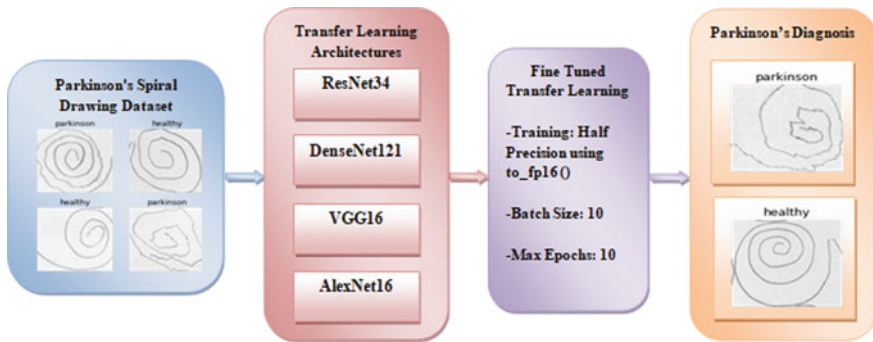

Fig. 1 Sample images from the dataset

Fig. 2 Workflow of automated Parkinson's disease diagnosis system

3.2 Methodology

The workflow of the automated Parkinson's disease diagnosis system is shown in Fig. 2. The publically available Parkinson's spiral images dataset has been used in this study. This is a balanced dataset with 51 spiral images from PD patients and the remaining 51 images from healthy individuals. ResNet 34, DenseNet 121, VGG16 and AlexNet transfer learning architectures have been used to classify spiral images. Accuracy, sensitivity, specificity, and ROC-AUC parameters are taken to analyze the performance of transfer learning architectures. All the transfer learning architectures were then fine-tuned and AlexNet outperforms with the best results in all performance measures.

4   Results and Discussions

The paramount goal of this research is to design a PD diagnosis system using a spiral drawing of PD patients. The performance of the four transfer learning techniques namely ResNet34, DenseNet121, VGG16, and AlexNet are measured in terms of accuracy, specificity, and sensitivity as defined below.

$$\text{Accuracy} = \left(\frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \right) *100$$

$$\text{Specificity} = \left(\frac{\text{TN}}{\text{TN} + \text{FP}} \right) *100$$

$$\text{Sensitivity} = \left(\frac{\text{TP}}{\text{TP} + \text{FN}} \right) *100$$

Here.

TP (True Positive): The individual is Parkinson's patient and the model has also detected it as Parkinson's patient.

TN (True Negative): The individual is healthy and the model has also detected it as healthy.

FP (False Positive): The individual is healthy and the model has detected it as Parkinson's patient.

FN (False Negative): The individual is suffering from Parkinson's and the model has detected it as healthy.

In all the transfer learning models used, CNN networks were used as a backbone with a fully connected head and a single hidden layer as a classifier. In the starting initial layers were frozen and weights are learned on the last fully connected layers means only the classification layer was trained. Then by running and experimenting with different epochs, architectures were saved when the best results were achieved. Finding the correct learning rate plays an important role in transfer learning architectures. Then the best learning rate was obtained by a function called lr_find. After that, all the layers were unfreezing and architectures were trained with the best learning rate. The batch size is taken as 10 during the training phase.

It was seen that as the number of batches escalated, the training and validation loss plummeted. The training and validation loss versus batch process for the ResNet34, DenseNet121, VGG16, and AlexNet are shown in Figs. 3, 4, 5 and 6 respectively. The performance of any classification model can be evaluated by confusion matrix. It is an M by M matrix in which M is the output class number. This matrix is drawn between the actual value and predicted value. The Confusion matrix for ResNet34, DenseNet121, VGG16, and AlexNet are shown in Figs. 7, 8, 9 and 10 respectively.
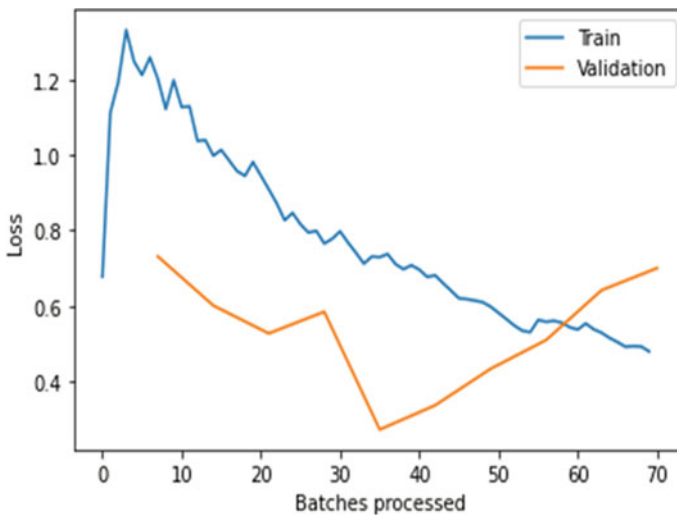
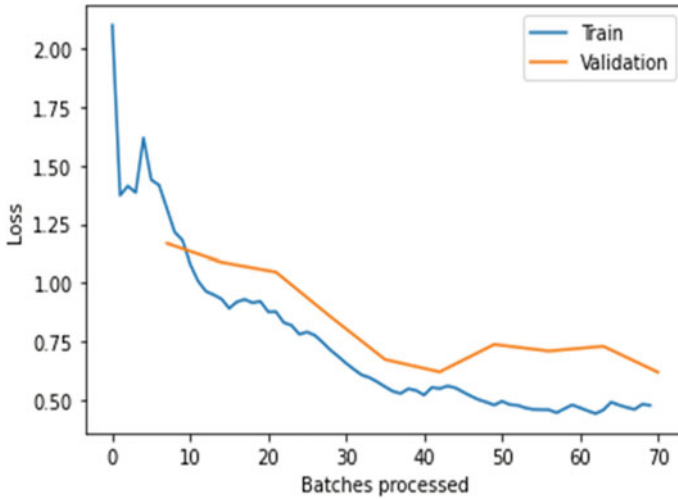**Fig. 3** ResNet34-Train and validation loss

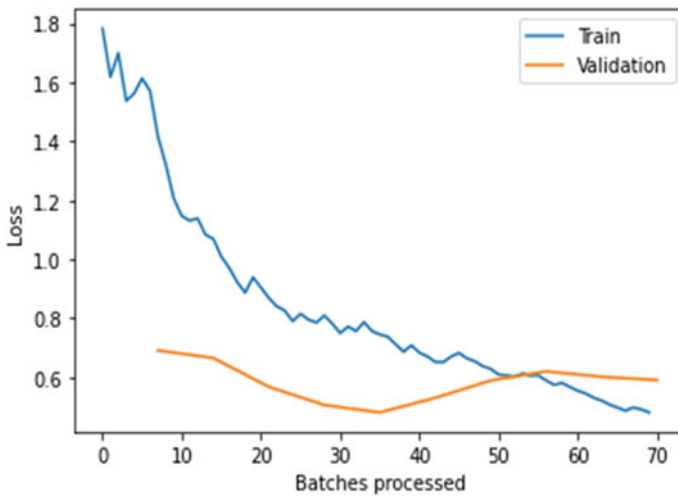**Fig. 4** DenseNet121-Train and validation loss


Fig. 5 VGG16- Train and validation loss

The performance of transfer learning architectures is shown in Table 1. After fine-tune, ResNet Architecture gives 90% accuracy, 86.66% specificity and 93.33% sensitivity. The DenseNet architecture gives 86.66% accuracy, 86.66% sensitivity, and 86.66% specificity. The VGG16 architecture gives 83.33% accuracy, 73.33% sensitivity, and 93.33% specificity. AlexNet architecture outperforms with 93.33% accuracy, 93.33% sensitivity, and 93.33% specificity as shown in Fig. 11.
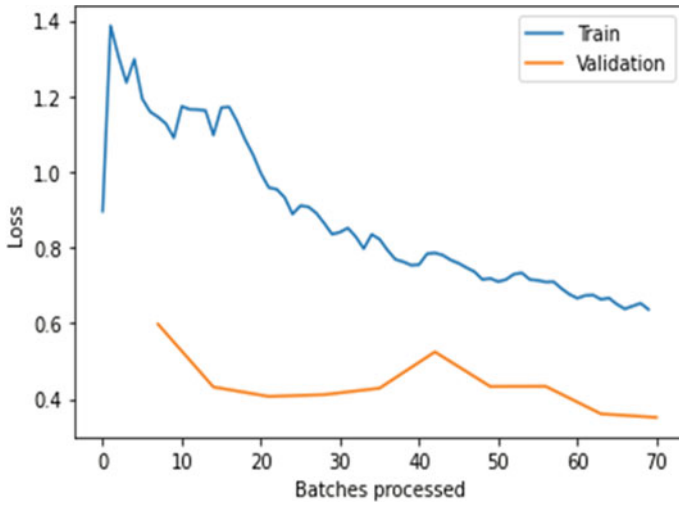
Fig. 6 AlexNet-Train and validation loss

Fig. 7 ResNet34-Confusion
matrix
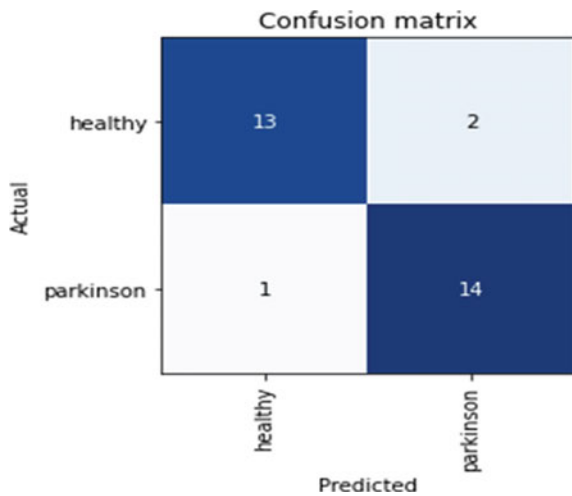
ROC is a graphical 2-D plot drawn between the true-positive rate and false-positive rate. Under this performance metric, the area under the curve (AUC) is calculated which lies between zero to one. AUC of the transfer learning architectures is been measured and shown with this graph. The higher the AUC means the model is more efficient to classify the spiral images drowned by PD patients and healthy individuals. ROC curve of transfer learning architecture is shown in Fig. 12.

Due to technological enhancement, computer-assisted medical diagnosis systems are gaining momentum as medical resources are limitedly available in developing
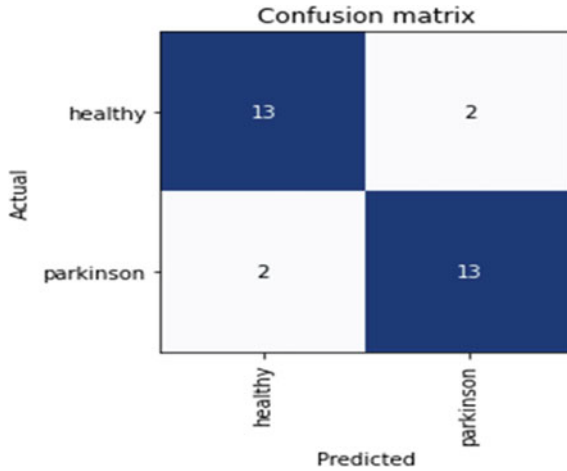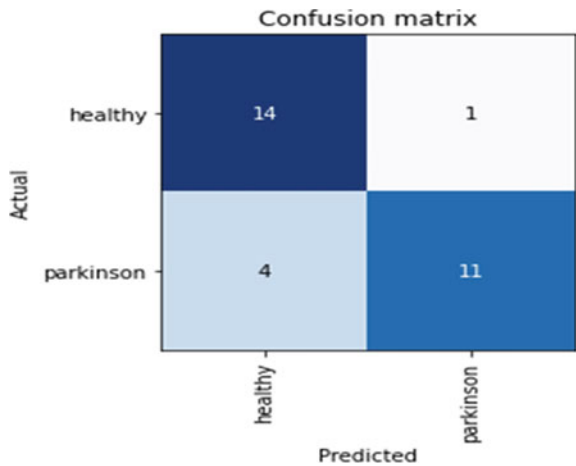
Confusion matrix

Fig. 8 DenseNet121-Confusion matrix

Fig. 9 VGG16-Confusion matrix

countries like India. The results are propitious and advocate that the proposed automated system can be used for PD diagnosis but it has some limitations.

The presented automated system is not able to find the severity of Parkinson's disease; it can only classify spirals drown by PD patients and healthy individuals.

There is a need to test this automated system on other Parkinson's drawing datasets for a reliable diagnosis.
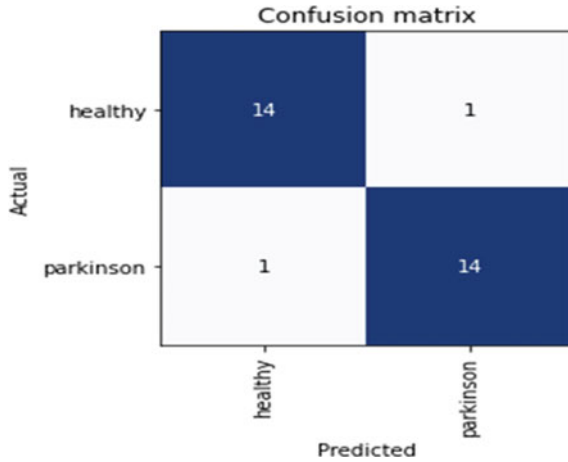
Confusion matrix

Fig. 10 AlexNet16-Confusion matrix

Table 1 Performance comparison of fine-tuned transfer learning architectures

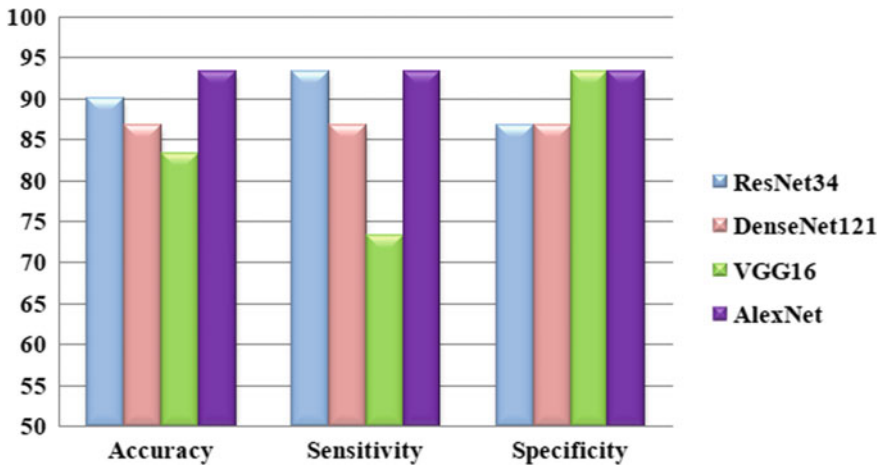| Model	Accuracy %	Sensitivity %	Specificity %
ResNet34	90.00	93.33	86.66
DenseNet121	86.66	86.66	86.66
VGG16	83.33	73.33	93.33
AlexNet	**93.33**	**93.33**	**93.33**

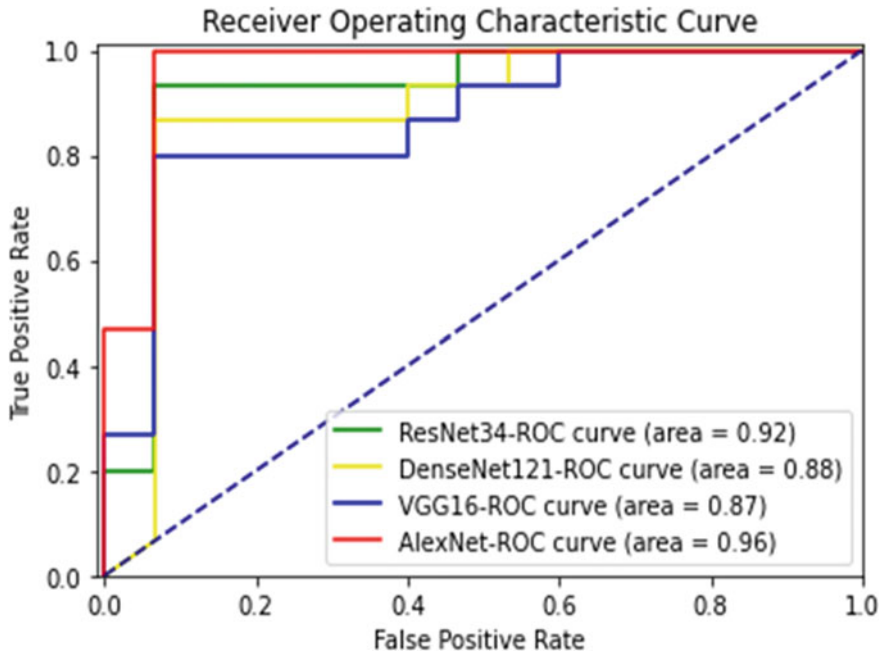**Fig. 11** Performance comparison of transfer learning architectures

Fig. 12 ROC curve

5 Conclusion and Future scope

Parkinson's disease is a chronic disease that is progressive in nature and its symptoms appear over time. Initial symptoms are mild and as the disease goes forward the symptoms become critical. The life of Parkinson's patients is badly affected by this disease, in some of the cases patient is not easily able to do some of the daily needs works like writing or typing, eating food, walking up from the bed and washing dishes, etc. Since the disease is incurable, its timely diagnosis can improve the patient's life. An automated Parkinson's disease diagnosis system is presented in this research work by applying deep learning techniques on spiral images. The performance of four transfer learning architectures was analyzed. AlexNet architecture outperforms with the highest 93.33% accuracy and 0.96 AUC. The authors plan to test the presented automated system on other Parkinson's drawing datasets like wave, meander, and circles in near future. The authors also plan to develop a deep learning-based Parkinson's disease diagnosis system using MRI images.

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