2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) | 978-1-6654-3521-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICSES52305.2021.9633872

Parkinson's Disease Detection Using CNN Architectures with Transfer Learning

Nusrat Jahan, Arifatun Nesa and Md. Abu Layek*

Department of Computer Science and Engineering Jagannath University, Dhaka, Bangladesh
E-mail: nusratjahan.cse19@gmail.com arifatun.cse.15.jnu@gmail.com layek@khu.ac.kr

Abstract: -Nowadays the most common and incurable neurological disorder disease is Parkinson's disease (PD). This incurable disease is growing terribly. This study determines PD patients on the basis of fine motor symptoms using sketching. We proposed a system where we use spiral and wave sketching that can identify either the sketch is from a PD patient or not. Our experiment was done on a dataset consisting PD patient and Healthy (without PD) control group. We applied a deep learning approach Convolutional Neural Network (CNN) to determine PD infected patients and healthy (without PD) control group. We experimented on two CNN models - Inception v3 and ResNet50, with transfer learning method. The proposed system achieved 96.67% accuracy on the Inception-v3 model with spiral sketching.

Keywords—Parkinson's Disease, PD, Deep Learning, CNN, Transfer learning

I. INTRODUCTION

According to a recent study, there are more than seven million Parkinson's disease (PD) patients worldwide [1]. The name of Parkinson's disease comes from James Parkinson who described this disease at first. Among people over the age of 50, the disease is the most common. Spiral sketching, wave sketching, and handwritten texts could be easily distinguished of a healthy (without PD) person and a PD infected person and the measurement of those sketching & handwriting are non-invasive [2]. Symptoms of Parkinson's disease are widely divided into two classes; Non-motor and Motor symptoms. Motor symptoms are the tremor that is inadvertent movement of the legs, hands, stiffness meaning difficulty in moving the parts of the body, slowness in regular functions, shuffling gait, disability in balance. Non-motor symptoms are eyesight, speech and swallowing problems, slowness of thought, insomnia and fatigue, struggling with memory, disquietude, dejection, hallucinations and delusions, [3]. Parkinson's disease motor symptoms causes three issues in the case of writing [4]: micrographia [5], pen-pressure [6] and kinematics. This paper deals with motor symptoms such as tremors by recognizing the drawings from Parkinson's and healthy (without PD) subjects.

A well-known fact is that generalizing neural networks with the same design can be used to solve different problems [7]. This study worked with sketched data that performed by the healthy (without PD) group and PD group and used existing CNN model for classification purposes. The orientation of rest of this paper is as follows. Section 2 illustrate the related works and section 3 illustrate the methodology of the study. Section 4 illustrate the experiment and results analysis. Section 5 illustrate the discussion and section 6 illustrate the conclusion in this study.

II. RELATED WORK

In this section, we discussed few works related to the diagnosis of Parkinson's disease which is based on the machine learning and deep learning techniques using different types of datasets.

A. Machine Learning approaches with Spiral Drawing

Spiral sketching images was used in this study to detect Parkinson's disease. Zham, P. et al. [8] proposed a method with two eminent features of spiral sketching images. One is speed, and another is pen pressure. For classification they used Naïve Bayes classifier. Using Direction and Angular change of features for Archimedean guided spiral, they distinguished of PD groups and healthy Control groups. The authors showed that PD patient's can be separated effectively from the control group with area under the curve (AUC) value 0.933.

B. CNN approaches using drawing movements

Gil-Martín, M. et al. [5] utilized the directional information of the drawing movements to detect PD patient. They used Fast Fourier transform in the input and then applied CNN method where the model was divided into two-parts. The first part is convolution layer which used for feature extraction and then the second part is a fully connected layer used for classification. They obtained 96.5% accuracy, 97.7% F1-score.

C. ML approaches using drawing movements

Detection method based on the sketching simple horizontal line were proposed by Kotsavasiloglou, C. et al.[9]. Sketching was taken from the healthy (without PD) subjects and PD patients on the surface of pad. They used machine learning algorithms for classification to identify the curved movements. To develope an automated system, the authors utilized a set of classifiers at the training stage. They obtained an accuracy of 91%.

D. Multistage Classifier approaches using Wave and Spiral Drawings

Chakraborty, S. et al. [10] proposed a CNN method and machine learning classifiers. They used both wave and spiral sketching datasets on which the CNN model was run. They calculated the probability score from CNN model and then pass through on the LR (Linear Regression) and RFC (Random Forest Classifier) ensemble classifiers. The clasifiers gives a prediction value. Then, they used weighted average voting to combine wave and spiral sketch prediction results. They obtained 93.3% accuracy in their model.

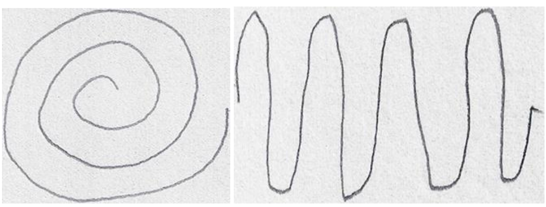
E. Transfer Learning

In deep learning to work with small and unlabeled datasets is the most challenging issue. Transfer learning can handle a limited dataset in a research problem. When a new task is learned by transferring knowledge from an old task is referred to as transfer learning. It stores knowledge gained from an old task with a large benchmark dataset and then apply these knowlwdge to a new model where we have the limited datasets. There are two principal techniques to implement transfer learning. One is Feature Extraction; the Convolutional layer is pre-trained without the fully connected layer. This pre-trained part works like a fixed feature extractor for the fresh job. Another strategy is the Fine-Tuning where full or some of the layers are re-trained on the new dataset along with the pre-trained Convolutional layers. In this case, we can freeze several layers for keeping fix weight and then fine-tuning is applied on the remaining layers. The weights are updated by backpropagation [11, 12].

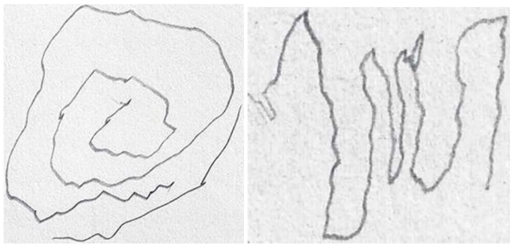
III. METHODOLOGY

A. Datasets

We collected our datasets from the Kaggle [13] consisting of wave and spiral sketch drawings from 55 subjects. Among the 55 subjects, 28 were collected from the healthy (without PD) control group and 27 from the PD patients. In the dataset there are 204 drawing images equally from wave and spiral sketching where many subjects have multiple sketches. To record sketching image, A3 size paper, and a pen were used [10]. Figure 1 shows sample Images of the sketches for PD and Healthy (without PD) groups from the datasets.



(a) Spiral and Wave Image of Healthy (without PD)

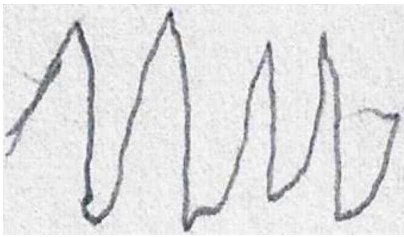


(b) Spiral and Wave Image of Parkinson

Figure 1: Sample of the dataset

B. Data Preprocessing

We applied data thinning process to the dataset using "Zhang-Suen algorithm" [14]. Since we only consider the structure of sketching rather than pressure sensitivity, the data needs to be clear. The sketches were drawing with different types of pencils. As a result, the performance of the dataset gets affected. By applying thinning process, the thickness of the drawing as well as shape become uniform to classify the healthy (without PD) and PD groups. Figure 2 shows a sample sketched image and the thinned version. Data images have been resized for study. The spiral images have been resized to 256 × 256 and the wave images have been resized to 512 × 256 (height × width).



(a) Before Thinning

(b) After Thinning

Figure 2: Sample sketching images of thinning

For the preparation of data, we applied image augmentation on all images using the on-the-fly techniques. If the number of data in the dataset is less, then it becomes quite difficult to apply CNN. As our number of the dataset is quite small, therefore, using image augmentations we created some synthetic sample data/image increased the working dataset size.

Several parameters for image augmentation have been applied to the data with distinct value for both wave and spiral sketching. Table I and Table II list up these image augmentation parameters with their corresponding values

Table I: The Parameters of Data Augmentation for Spiral Sketching

Parameters Name	Value
Height Shift	0.1
Width Shift	0.1
Zoom	0.2
Shear	0.2
Vertical Flip	Yes
Horizontal Flip	Yes
Rotation	360
Brightness	(0.5, 1.5)

C. Model Development

We divided our model structure into three stages. In the first stage, we processed our dataset by thinning and augmentation. Then in the second stage, we performed transfer learning. We used two CNN architectures: ResNet 50 and Inception V3. The architectures were pre-trained by imagnet dataset (large visual database). As our dataset size too small that's why these pre-trained models will give the knowlwdge that will help for performing detection. For the pre-trained model, we freeze the top layers of both CNN architectures and stored the knowledge. In the final stage, we perform fine-tuning in the fully connected layers of these architectures with the pre-processed dataset. Finally, the model can identify healthy people and Parkinson disease infected people. Figure 3 depits the working flow of the proposed model.

Table II: The Parameters of Data Augmentation for Wave Sketching

Parameters Name	Value
Height Shift	0.1
Width Shift	0.1
Zoom	0.2
Shear	0.2
Vertical Flip	Yes
Horizontal Flip	Yes
Rotation	5
Brightness	(0.3, 1.8)

IV. Results And Analyses

We calculated accuracy of the ResNet50, Inception-v3 models with various learning rates: 1e-5, 3e-5, 3.15e-5, 3.5e-5, 4e-5 and recorded gains and losses of these model on sketching image data. Table III, IV shows the accuracy and loss values respectively for ResNet50 and Inception v3 using transfer learning.

From these tables, we can see that performance of the models varies significantly based on the sketching styles; models perform better with spiral sketching than the wave. Then we analysed on the spiral sketching. Later on, the accuracy of spiral sketching of two models is compared.

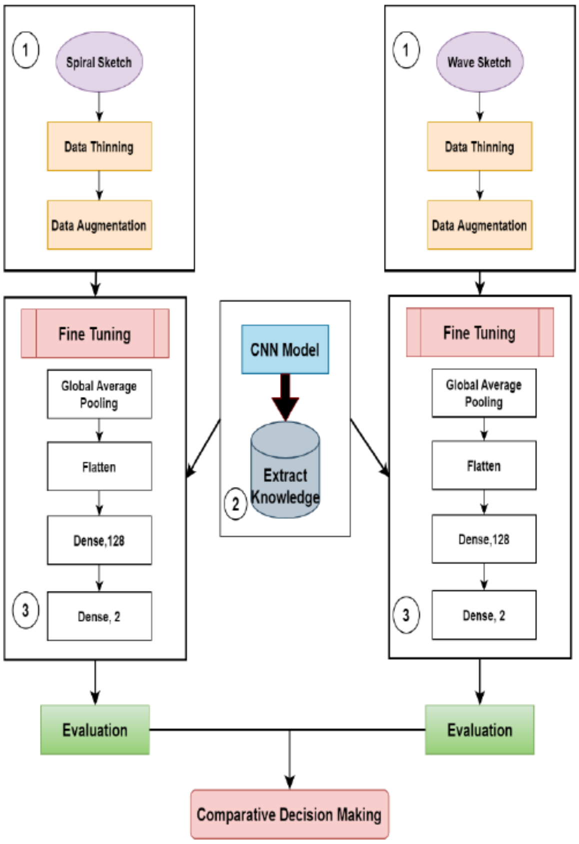


Figure 3: Working Flowchart of our Proposed System

Table III: Accuracy and Loss on Test Images in ResNet50

Leaning rate	Spiral	Wave
1e-5	loss: 20.13%	loss: 26.74%
	accuracy: 93.33%	accuracy: 90%
3e-5	loss: 12.61%	loss: 21.84%
	accuracy: 96.67%	accuracy: 90%
3.15e-5	loss: 14.66%	loss: 28.66%
	accuracy: 96.67%	accuracy: 86.67%
3.5e-5	loss: 11.97%	loss: 23.28%
	accuracy: 96.67%	accuracy: 83.33%
4e-5	loss: 12.30%	loss: 31.21%
	accuracy: 96.67%	accuracy: 86.67%

Table IV: Accuracy and Loss on Test Images in Inception v3

Leaning rate	Spiral	Wave
1e-5	loss: 20.88%	loss: 51.29%
	accuracy: 96.67%	accuracy: 76.67%
3e-5	loss: 12.47%	loss: 25.31%
	accuracy:	accuracy:

	96.67%	76.67%
3.15e-5	loss: 7.28%	loss: 27.654%
	accuracy: 96.15%	accuracy: 61.53%
3.5e-5	loss: 1.71%	loss: 35.39%
	accuracy: 96.67%	accuracy: 76.67%
4e-5	loss: 1.51%	loss: 30.48%
	accuracy: 96.67%	accuracy: 80%

It is noticeable that the evaluation of these models provides almost the same accuracy for some learning rates (Figure 4). But there have some significant changes in the loss function. According to the loss function graph (Figure 5), it is clear that the Inception-v3 model provides a lower amount of loss for learning rate 4e-5 than the Resnet50 model and also provides better accuracy.

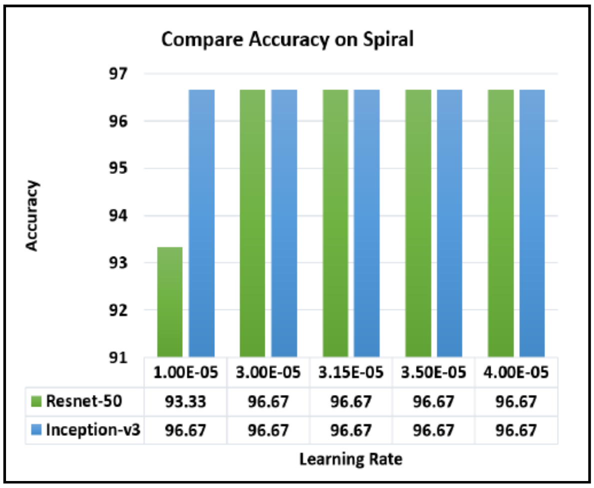


Figure 4: Accuracy comparison on Spiral among CNN Architectures

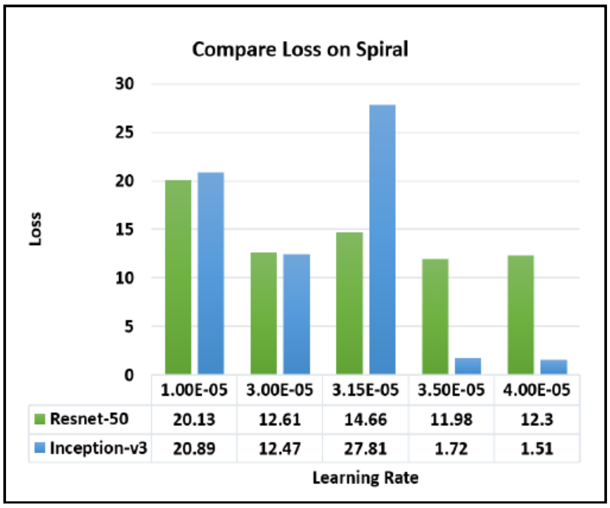
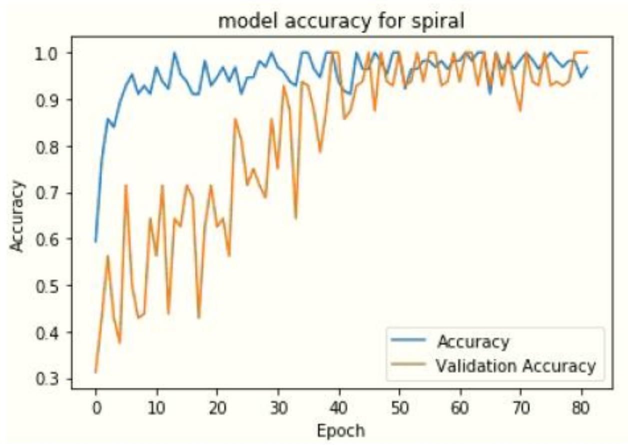


Figure 5: Loss comparison on Spiral among CNN Architectures

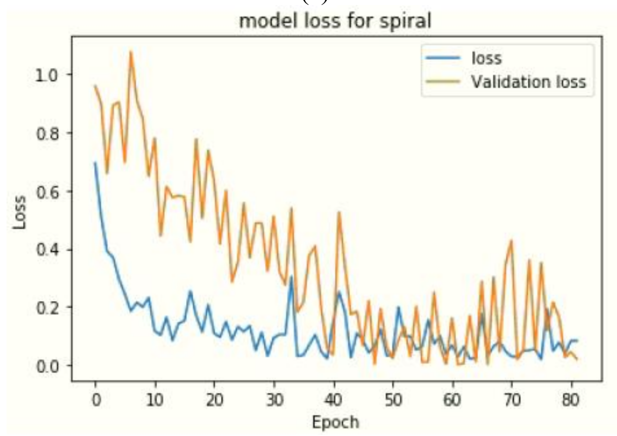
V. DISCUSSION

This study proposed a model that Inception-v3 for learning rate 4e-5 provides 96.67% accuracy with a lower amount of loss. Figure 6a and 6b are shown the performance graph of the Inception-v3 models for learning rate 4e-5. Figure 6a represent the model accuracy of Spiral sketching and 6b represents the model loss of Spiral sketching. We get 93.33% precision, 100% recall and 96.55% F1 score of this model. Figure 7 shows the Confusion Matrix of Inception-v3 for learning rate 4e-5.

Finally, the test result of the proposed model is compared with some other models. After testing data images on the proposed model Inception-v3, it has scored 96.67% on spiral image samples. It makes a comparative decision based on how accurately Parkinson's disease can be detected. Table V shows that our proposed model gives better accuracy than another existing models.



(a)



(b)

Figure 6: (a) Inception-v3 model accuracy on spiral sketch (b) Inception-v3 model loss on spiral sketch

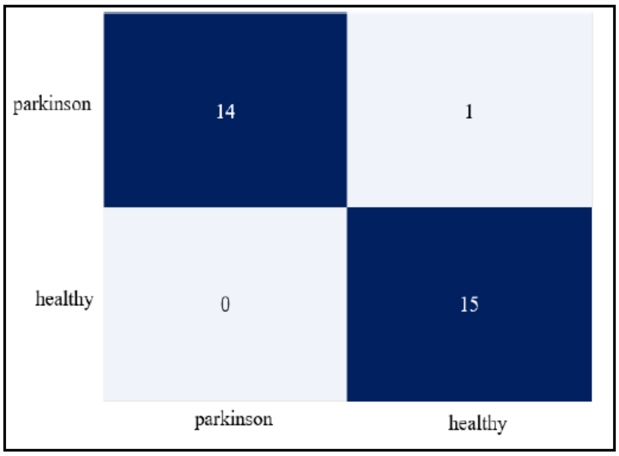


Figure 7: Confusion Matrix on Inception-v3 model

Table V: Comparison of accuracy between previous and proposed method

Authors & Proposed method	**Accuracy**
Kotsavasiloglou, C. et al. [9]	91%
Zham, P. et al. [8]	93.3%
Chakraborty, S. et al. [10]	93.3%
Gil-Martín, M. et al. [5]	96.5%
Proposed Method	96.67%

VI. CONCLUSION

In this paper, a system is proposed to identify whether a person is a Parkinson's patient or not by examining the drawing sketches. In case of sketching, this study emphasizes on spiral sketches performed by healthy (without PD) subjects and PD patients for classification purposes. We suggested using transfer learning with CNN architecture: Inception-v3 model provides efficient result in distinguishing the sketches made by healthy subject (without PD) and PD patients.

We say the main limitation in this study that is lack of dataset. As we depended on the existing CNN method, we will try to work with a new architecture using transfer learning in future.

ACKNOWLEDGMENT

This work was supported by the Information Technology Research and Resource Center (ITRRC, http://itrrc.com), and the JnU research grant (জবি/গবিষণা/গপ্র/২০২০-২০২১/বিজ্ঞান/৩৩) Jagannath University, Dhaka, Bangladesh. Dr. Md. Abu Layek is the corresponding author.

REFERENCES

[1] "World Brain Day: Hot Topics in Parkinson Disease," Neurology live. https://www.neurologylive.com/view/world-brain-day-hot-topics-in-parkinson-disease (accessed Sep. 18, 2021).

[2] D James Surmeier, Jaime N Guzmán, Javier Sánchez-Padilla, and Joshua A Goldberg. What causes the death of dopaminergic neurons in parkinson's disease? Progress in brain research, 183:59–77, 2010.

[3] Tamanna Sood and Padmavati Khandnor. Classification of parkinson's disease using various machine learning techniques. In an International Conference on Advances in Computing and Data Sciences, pages 296–311. Springer, 2019.

[4] Poonam Zham, Dinesh K Kumar, Peter Dabnichki, Sridhar Poosapadi Arjunan, and Sanjay Raghav. Distinguishing different stages of parkinson's disease using composite index of speed and pen-pressure of sketching a spiral. Frontiers in neurology, 8:435, 2017.

[5] Manuel Gil-Martín, Juan Manuel Montero, and Rubén San-Segundo. "Parkinson's disease detection from drawing movements using convolutional neural networks." Electronics 8.8 (2019): 907.

[6] Peter Drot´ar, Ji˘r´ı Mekyska, Irena Rektorov´a, Lucia Masarov´a, Zden˘ek Sm´ekal, and Marcos Faundez-Zanuy. Evaluation of handwriting kinematics and pressure for differential diagnosis of parkinson's disease. Artificial intelligence in Medicine, 67:39–46, 2016.

[7] Qing Li, Weidong Cai, Xiaogang Wang, Yun Zhou, David Dagan Feng, and Mei Chen. Medical image classification with convolutional neural network. In 2014 13th international conference on control automation robotics & vision (ICARCV), pages 844–848. IEEE, 2014.

[8] Poonam Zham, Sridhar P Arjunan, Sanjay Raghav, and Dinesh K Kumar. Efficacy of guided spiral drawing in the classification of parkinson's disease. IEEE journal of biomedical and health informatics, 22(5):1648– 1652, 2017.

[9] C Kotsavasiloglou, N Kostikis, Dimitrios Hristu-Varsakelis, and M Arnaoutoglou. Machine learning-based classification of simple drawing movements in parkinson's disease. Biomedical Signal Processing and Control, 31:174–180, 2017.

[10] Sabyasachi Chakraborty, Satyabrata Aich, Eunyoung Han, Jinse Park, Hee-Cheol Kim, et al. Parkinson's disease detection from spiral and wave drawings using convolutional neural networks: A multistage classifier approach. In 2020 22nd International Conference on Advanced Communication Technology (ICACT), pages 298–303. IEEE, 2020.

[11] D. Sarkar, "A comprehensive hands-on guide to transfer learning with real-world applications in deep learning," Towards Data Science. Saatavissa: https://towardsdatascience.com/a-comprehensive-handson-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a. Hakupäivä, vol. 20, p. 2020, 2018.

[12] Maolin Yang, Auwal H Abubakar, Pingyu Jiang, 2021, Deep learning and complex network theory based analysis on socialized manufacturing resources utilisations and an application case study, Concurrent Engineering, Volume: 29 issue: 3, page(s): 236–248.

[13] K.Scott Mader. "Parkinson's Drawings." https://kaggle.com/kmader/parkinsons-drawings (accessed Sep. 18, 2021).

[14] TY Zhang and Ching Y. Suen. A fast parallel algorithm for thinning digital patterns. Communications of the ACM, 27(3):236–239, 1984.