International Journal of Computer Vision and Signal Processing, 11(1), 17-23(2021) ORIGINAL ARTICLE

Parkinson's Disease Detection Using ResNet50 with Transfer Learning

Nusrat Jahan, Arifatun Nesa

Department of Computer Science and Engineering, Jagannath University, Dhaka, Bangladesh

Md. Abu Layek*

Department of Computer Science and Engineering, Jagannath University, Dhaka, Bangladesh

Abstract

Parkinson's disease (PD) is an incurable neurological disorder disease. But there is still no standard medical provision to identify Parkinson's disease. In this study, a fine motor symptom that is sketching has been studied. The experiments are done on a significant number of PD patients and Healthy Group (without PD). We proposed a system that can determine the sketching and reports whether a PD patient's sketch or not. Deep learning algorithms can deal with the solution of different brain generalizing neural networks with the same design. Thus, we applied Convolutional Neural Network (CNN) to classify sketched images to discriminate or identify Parkinson's Disease (PD) affected patients from the regular healthy (without PD) control group. The experiment was done on different CNN models with transfer learning method and applying on Spiral and Wave sketched data. The proposed system achieved 96.67% accuracy on the ResNet50 model with spiral sketching.

Contribution of the Paper: The main contribution of this paper is, we have used Transfer learning which enhanced the model performance.

Keywords: Parkinson's Disease, Deep Learning, Convolutional Neural Network, Transfer Learning

IJCVSP

ISSN: 2186-1390 (Online)
http://cennser.org/IJCVSP

Article History:
Received: 30 March 2021
Revised: 21 July 2021
Accepted: 25 August 2021
Published Online: 26 August 2021

1. INTRODUCTION

In this era, more than seven million people worldwide are affected by Parkinson's disease (PD), according to a recent study [1]. Nowadays, this incurable disease is increasing tremendously. This disease gets its name from James Parkinson, who earlier described it as a paralysis agitans and later gave his surname was known as a PD. Parkinson's disease causes a diverse set of symptoms ranging from tremor to cognitive impairment, hallucination, dementia, sleep disorders, etc. It is the most common neurodegenerative disease among aged people who are more than 50 years old. Till now, there is no complete cure. This paper aims the predict Parkinson's disorder. To avoid the significant negative impact on PD patients, identification of PD in the premier stage is mandatory.

Previous clinicians and researchers already used Handwriting and Spiral sketching to identify PD patients successfully in the premier stages [2, 3]. Spiral and wave sketching, and handwriting could be easily differentiated from healthy person (without PD) to a person affected by PD and the measurement of those sketching & handwriting are non-invasive [4]. Parkinson's disease symptoms are broadly divided into two groups. One is Motor symptoms another one is Non-motor symptoms. Motor symptoms are tremor (involuntary movement of the legs/ hands), stiffness(difficulty in moving the parts of the body), slowness in daily activities, impaired balance, shuffling gait. On the other hand, non-motor symptoms are difficulties with memory, slowness of thought, anxiety and depression, insomnia and fatigue, vision problem, hallucinations and delusions, speech and swallowing problems [5]. Parkinson's disease with motor symptoms causes three main changes

*Corresponding author
Email addresses: nusratjahan.cse19@gmail.com (Nusrat Jahan), arifatun.cse.15.jnu@gmail.com (Arifatun Nesa), layek@khu.ac.kr (Md. Abu Layek)

in writing [2]: the size of writing [6] (micrographia [7]), pen-pressure [8] and kinematics. This paper works on motor symptoms which as tremors by recognizing drawing between healthy and Parkinson subjects.

Thus, this paper based on binary classification is developed to detect Parkinson's Disease by taking advantage of Convolutional Neural Networks. This study mainly leverages sketched data performed by healthy subjects and Parkinson's patients and used built-in Convolutional Neural Networks for classification purposes. The orientation of the paper is organized in the following way. Section 2 presents the related works. Section 3 presents the Convolutional Neural Network architecture used to build the proposed model. Section 4 presents the methodology of the study. Section 5 presents the experimental and result in analysis of the study. Section 6 presents the conclusion of this study.

2. RELATED WORKS

2.1. Speech Spectrogram-Based Deep Feature Assisted CAD

Zahid et al. [9] proposed three methods to develop a computer-aided diagnosis system.

1. Speech recordings using spectrograms are based on transfer learning.
2. Deep features extraction had been using several machine learning classifiers from speech spectrograms.
3. Machine learning classifiers further used for evaluation of simple acoustic features of those recordings.

This study was assessed on a Spanish dataset. They used the Alexnet model for handcrafted feature extraction and deep feature extraction. They also used transfer learning, deep feature, and acoustic-phonetic feature-based methods for classification purposes. The developed model achieved 99.7% accuracy on the pronunciation of vowel 'o' using a multi-layer Perceptron and achieved 99.1% accuracy on the pronunciation of vowel 'i' extracted deep features using random forest.

2.2. Dynamic handwriting analysis for the assessment of PD

Pirlo, G. et al. [10] proposed a Parkinson's disease detection system using Handwriting as a biomarker. This study has provided an online handwriting analysis to the assess of PD diseases from a pattern recognition perspective. They surveyed based on a pattern recognition perspective to describe different phases using handwriting as a biomarker.

2.3. Machine Learning-based classification using Spiral Drawing

Zham et al. [11] introduced a method to detect Parkinson's disease by sketching spiral images. In their study, they used two types of features. One is "Speed," another one is "Pen Pressure" while performing the sketch. After feature collection, they used the Naïve Bayes classifier. They showed that using Direction and Angular change both features for Archimedean guided spiral, PD and Control groups discrimination was most suitable. They analyzed in their study that the AUC curve of 0.933 indicates the differentiation of PD patients from the control group effectively.

2.4. Convolutional Neural Networks based approach using Drawing Movements

Gil-Martín et al. [12] detected Parkinson's disease based on different directions during the movement of drawing. There were using Fast Fourier's transform in input and applied on the CNN method. They divided the model into two-part where the first part consisted of a 2-layer convolution layer for feature extraction and the second part consisted of 3-layer fully connected layer for classification purposes. They obtained 96.5% accuracy, 97.7% F1-score.

2.5. Machine learning approach using drawing movements to detect Parkinson's disease

Kotsavasiloglou, C. et al. [13] proposed curved movement of the pen while sketching simple horizontal lines on the surface of the pad taken from the healthy and PD subjects. They used machine learning algorithms to differentiate the PD-affected group and healthy group. They applied different classifiers for the training purpose to develop an automated system. They achieved 91% accuracy.

2.6. Convolutional Neural Network and A Multistage Classifier Approach based approach using Spiral and Wave Drawings

Chakraborty, S. et al. [14] proposed a CNN method with multiple machine learning classifier. They worked with both spiral and wave drawing datasets collected from Kaggle's data repository. They proposed a CNN model that was run over these two different datasets, spiral and wave sketch datasets. They calculated the probabilities of prediction and then trained on ensemble classifier RFC (Random Forest Classifier) and LR (Linear Regression). Then they used weighted average voting to combine spiral and wave sketch testing results. They achieved 93.3% accuracy.

3. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURES

In this section, VGG16 and Resnet50 architectures are discussed, which are used in this study. These CNN architectures have succeeded in competitions such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [15].

3.1. *VGG16*

VGG16 (Visual Geometry Group) is a convolutional neural network (CNN) architecture that is developed by oxford and won the ILSVR (ImageNet) competition in 2014. It is also called OxfordNet. This architecture consists of 13-convolutional layers and 3-fully connected layers. The input size is the default, and it is 224 × 224 RGB images. There has a fixed 3 × 3 filter size in convolutional layers [16]. Figure 1 shows VGG16 architecture.

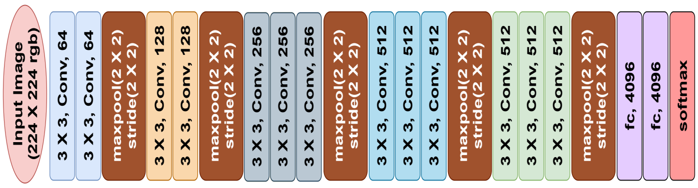


Figure 1: VGG16 Architecture

3.2. *ResNet50*

ResNet50 has 50 layers with 25 million parameters. In 2015, ResNet was the winner of the ImageNet challenge. It can train extremely deep neural networks successfully [17]. Residual learning tries to learn some residual instead of trying to learn some features. ResNet used shortcut connections and created a residual block. The residual intermediate block learns how to adapt with input for high-quality features. ResNet is introducing a "identity shortcut connection" which skips one or more layers. Figure 2 shows ResNet 50 architecture with two types of block; one is Convolutional block, and another one is identity block.

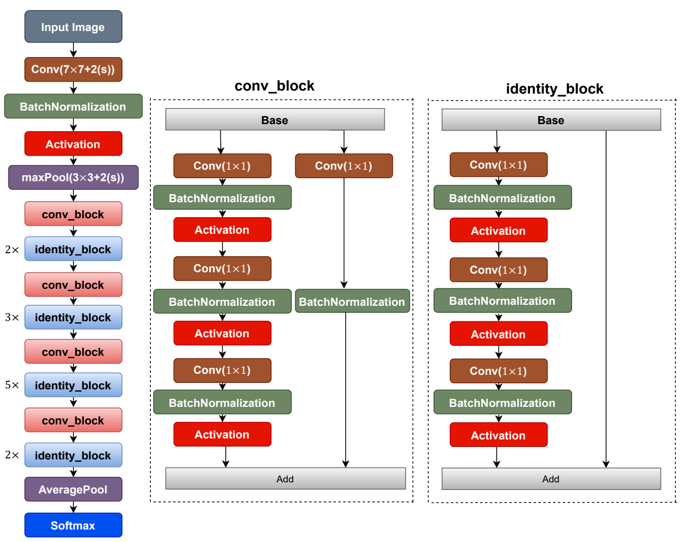


Figure 2: ResNet50 Architecture

3.3. *Transfer Learning*

Transfer learning is a well-known and prominent technique that can use as a pre-trained model. When a model was trained with large-size benchmark datasets (e.g. ImageNet dataset) to solve a problem then it's called a pre-trained model.Transferring knowledge of old tasks into a new job, when a new job is learned it is called transfer learning. We can reuse a model for different tasks by using transfer learning [18, 19]. Transfer learning is destined by domain and task. There has two elements in a domain – one is feature space (denoted by X) another one is probability distribution (denoted by P(X)).

$$D = \{X, P(X)\} \tag{1}$$

Here, $X = \{x_1, x_2, x_3 ....x_n\} \in X$.A task consists of two elements – one is Predictive Function "$f(x)$" another one is Label Space "y".

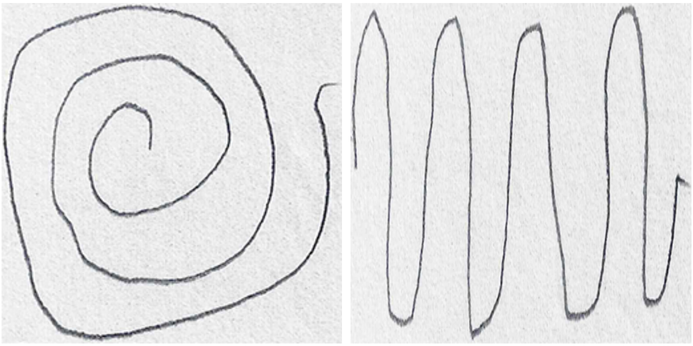
$$T = \{y, f(x)\} \tag{2}$$

Here, predictive function, "$f(x)$" predicts the corresponding label of a new instance x [20]. In deep learning, it is challenging to work with small and unlabeled datasets. Transfer learning has the advantage that is handling a limited dataset in a research problem by storing knowledge gained from a large benchmark dataset and then applying it to a model which deals with the limited dataset. There have two types of technique to implement transfer learning. They are Feature Extraction and Fine-Tuning. In the Feature Extraction, the ConvNet model is pre-trained on the large scale ImageNet dataset without the fully connected layer and the pre-trained ConvNet treat as a fixed feature extractor for the new task. By using pre-trained model's weights in a new task which is trained with new data. In Fine-Tuning strategy, not only pre-trained the Convolutional layers but also re-trained some of the layers on the new dataset. That means we can freeze some of the layers (can fix weight) and fine-tuning is used in the rest of the layers. In fine-tuning the weights are updated using backpropagation [21, 22].

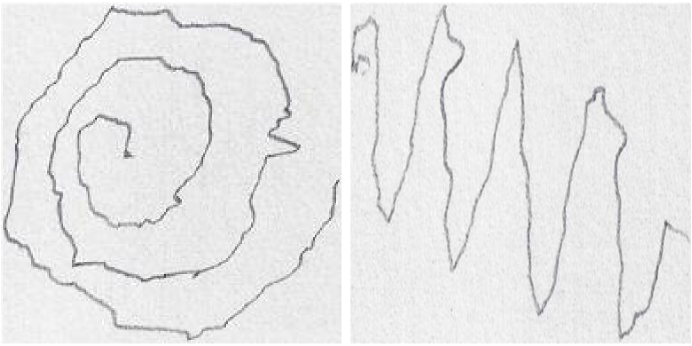
4. Methodology

4.1. *Data Collection*

We collected data from Kaggle's dataset [23]. This dataset is a set of spiral and wave sketches from 55 subjects where 28 subjects from the healthy control group (without PD) and 27 subjects from the Parkinson's group. The dataset contains 102 spiral sketching images and 102 wave sketching images. A tablet, A3 size paper, and a pen were used to record sketching [14]. Sample Images of the sketches for Healthy (without PD) and Parkinson Group are given in Figure 3.



(a) Healthy Spiral and Wave

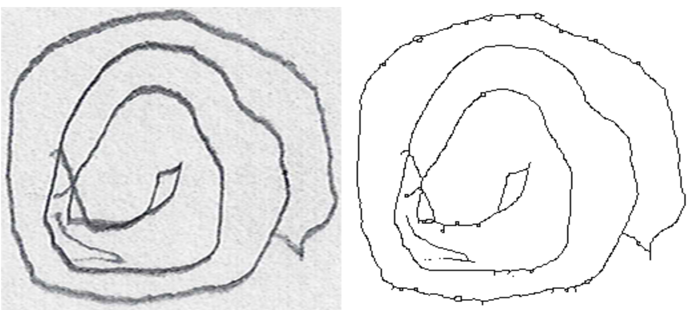


(b) Parkinson Spiral and Wave

Figure 3: The sample images of Healthy and Parkinson

4.2. Data Preprocessing

For the preparation of data, thinning was applied to the dataset. Zhang-Suen algorithm is a renowned algorithm that has been used for data thinning [24]. In this study, the structure of sketching was only considered rather than pressure sensitivity. Some of the image of the dataset create two edge line and has a thicker line. As a result, the training and testing performance on the dataset gets affected. By applying the Zhang-Suen thinning algorithm, the drawings become uniform in color, thinness, and shape become the dominant feature to classify the Healthy (without PD) and Parkinson group. A sample output of sketched images after thinning is given in Figure 4. The data images were resized for study. For Resnet 50, we resized the spiral sketches to 256 × 256 (height × width) and the wave sketches to 512 × 256 (height × width). For VGG16 spiral and wave both sketches were resized to 224 × 224 (height × width).



(a) Before Thinning (b) After Thinning

Figure 4: The sample images of Healthy and Parkinson

After resizing, all the images were augmented using the on-the-fly data augmentation technique. As our dataset number is relatively small, we performed image augmentations to induce some synthetic sample data/image in the dataset.

The number of Image data after performing augmentation using ImageDataGenerator in Keras can be evaluated using a specific formula given below.

$$GI = n_T \times n_E \quad (3)$$

Here, GI = Generated Image, n_T = Number of images in the Training set and n_E = Number of epochs specified during fit.

Table 1: The Parameters of Augmentation in Spiral Sketching

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

Several parameters for image augmentation we applied to the data. These parameters of image augmentation with the corresponding distinct value are given below in Table 1 and Table 2.

4.3. Model Development:

In this study, two types of CNN architecture are used – VGG16, ResNet50. These architectures are pre-trained by imagenet dataset and stored the knowledge. The spiral and wave images are preprocessed using data thinning and data augmentation. Then we applied fine tuning with this dataset using extracted knowledge. So, through this process, we applied transfer learning to CNN architectures. Figure 5 describes the functional flow of the proposed model. Then we figure out a comparative conclusion on spiral sketching and wave sketching.

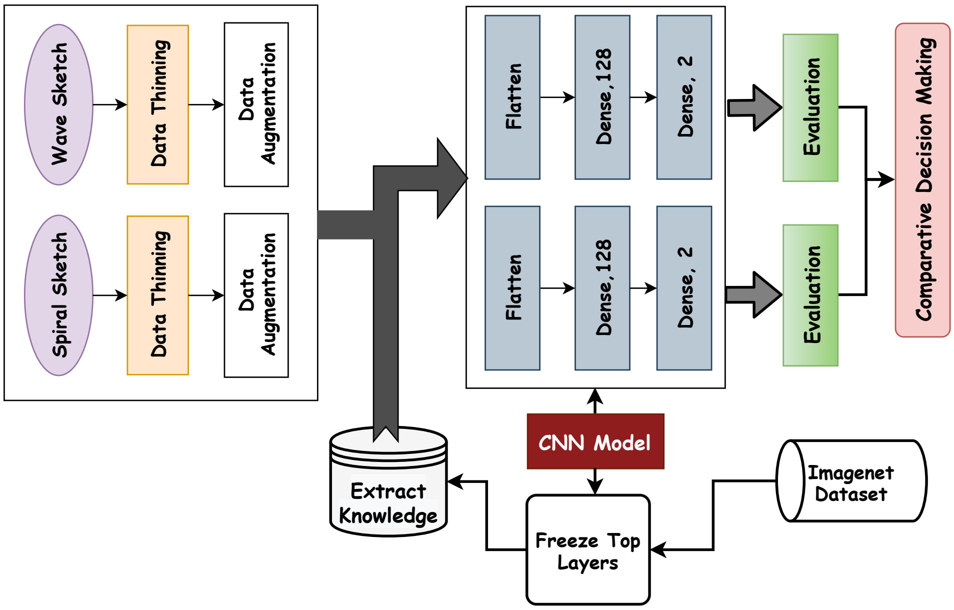


Figure 5: Working Flowchart of Proposed System

Table 2: The Parameters of Augmentation in Wave Sketching

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

5. EXPERIMENTAL AND RESULT ANALYSIS

5.1. Experimental Assesment

This study was calculated the accuracy of the model: VGG16, ResNet50 with different learning rates: 1e-5, 3e-5, 3.15e-5, 3.5e-5, 4e-5, and figure out various gains and losses of these model on spiral and wave sketching images data. Figure 6 shows the accuracy comparison for spiral and wave images on VGG16, ResNet50.

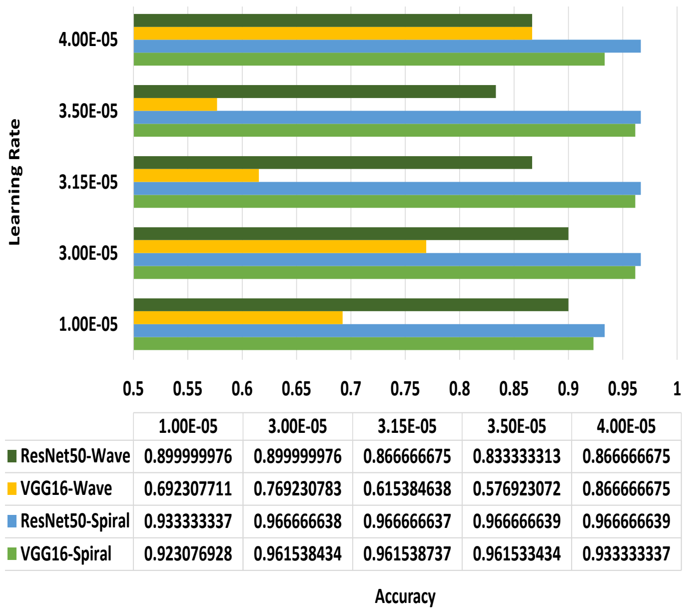


Figure 6: Accuracy comparison on Spiral and Wave images between CNN Architectures

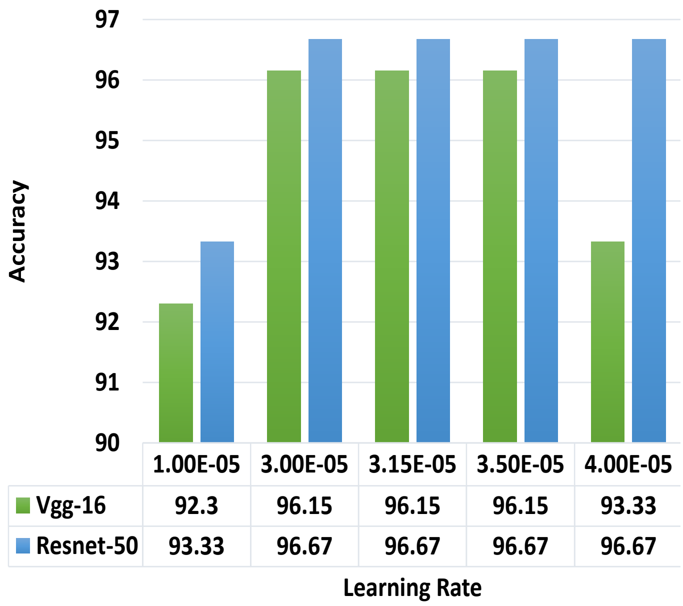


Figure 7: Accuracy comparison on Spiral images between CNN Architectures

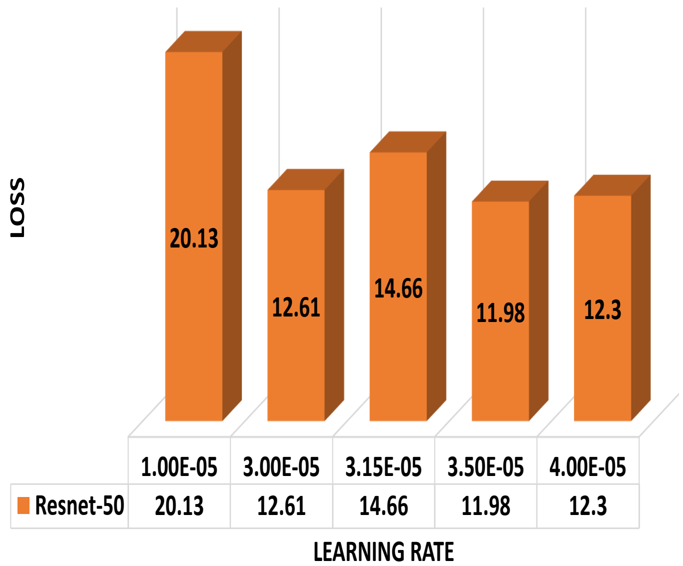
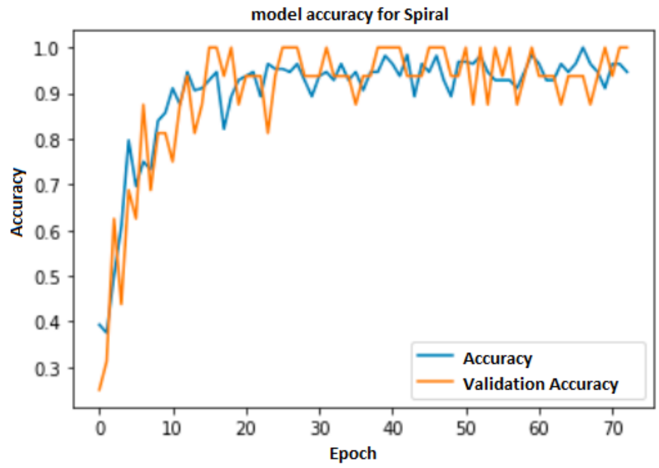
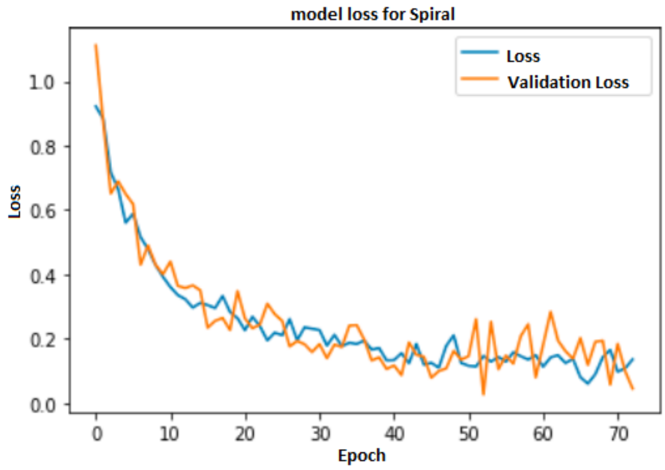


Figure 8: Loss comparison on Spiral images among learning rates of ResNet50



(a)



(b)

Figure 9: (a) ResNet50 model accuracy on the spiral sketch (b) ResNet50 model loss on the spiral sketch

Based on this figure, we see that the performance of models on spiral sketching provides better performance than wave sketching. So, the spiral sketching gives better performance than wave in the case of parkinson's disease detection. Then further analysis was done on the spiral sketching. Then we compared the accuracy of spiral sketching of these models. We see that the ResNet50 model provides better accuracy than VGG16 model. Figure 7 is shown the comparison. Then after evaluating on several learning rates of ResNet50, ResNet50 gives better accuracy is 96.67%, with a lower loss for learning rate 3.5e-5 (Figure 8).

So, this study found a model that is ResNet50 for learning 3.5e-5 which provides 96.67% accuracy. Figure 9 shows the performance graph of the ResNet50 model for learning rate 3.5e-5. Figure 9a represent the ResNet50 model accuracy of Spiral sketching, and Figure 9b represents the ResNet50 model loss of Spiral sketching.

We compared our accuracy with previous work. Author

Chakraborty et al. [14] worked with the same dataset and got 93.3% accuracy. Whereas we got 96.67% accurarcy. As we use the transfer learning method in the CNN model, it enhanced the model performance. So, this method gives better accuracy.

6. CONCLUSION AND FUTURE WORK

In this research, a system is developed to classify whether a person who attempted the sketching test is affected by Parkinson's disease or not based on Convolutional Neural Networks. The work mostly took advantage of spiral image data performed by healthy subjects and Parkinson's patients for classification purposes. This research proposed here transfer learning with CNN architecture. The approach that has been applied: ResNet50 model provides satisfactory result with 96.67% accuracy to distinguish the sketches made by healthy subjects and Parkinson's patients using transfer learning.

We will further improve the methodology and the performance of the classifier in this research. Though this study depends on built-in CNN architecture, there has a broad scope in the future to propose a new model using transfer learning. Also, improvement can be done on datasets with a wide variety of features that could play an important role to detect the disease.

7. ACKNOWLEDGMENT

This work was supported by the Information Technology Research and Resource Center (ITRRC, http://itrrc.com), and the JnU research grant (Jobi/GobeShona/Gopro/2020-2021/Biggan/33) Jagannath University, Dhaka, Bangladesh.

References

[1] A. Bigica, World brain day: Hot topics in parkinson disease, Neurology LiveRetrieved from.
URL `https://www.neurologylive.com/clinical-focus/world-brain-day-hot-topics-in-parkinson-disease.`

[2] P. Zham, D. K. Kumar, P. Dabnichki, S. Poosapadi Arjunan, S. Raghav, Distinguishing different stages of parkinson's disease using composite index of speed and pen-pressure of sketching a spiral, Frontiers in neurology 8 (2017) 435.

[3] M. San Luciano, C. Wang, R. A. Ortega, Q. Yu, S. e. a. Boschung, Digitized spiral drawing: a possible biomarker for early parkinson's disease, PloS one 11 (10) (2016) e0162799.

[4] D. J. Surmeier, J. N. Guzmán, J. Sánchez-Padilla, J. A. Goldberg, What causes the death of dopaminergic neurons in parkinson's disease?, Progress in brain research 183 (2010) 59–77.

[5] T. Sood, P. Khandnor, Classification of parkinson's disease using various machine learning techniques, in: International Conference on Advances in Computing and Data Sciences, Springer, 2019, pp. 296–311.

[6] A. R. Potgieser, E. Roosma, M. Beudel, B. M. de Jong, The effect of visual feedback on writing size in parkinson's disease, Parkinson's Disease 2015.

[7] A. Letanneux, J. Danna, J.-L. Velay, F. Viallet, S. Pinto, From micrographia to parkinson's disease dysgraphia, Movement Disorders 29 (12) (2014) 1467–1475.

[8] P. Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. e. a. Smékal, Evaluation of handwriting kinematics and pressure for differential diagnosis of parkinson's disease, Artificial intelligence in Medicine 67 (2016) 39–46.

[9] L. Zahid, M. Maqsood, M. Y. Durrani, M. Bakhtyar, J. e. a. Baber, A spectrogram-based deep feature assisted computer-aided diagnostic system for parkinson's disease, IEEE Access 8 (2020) 35482–35495.

[10] D. Impedovo, G. Pirlo, Dynamic handwriting analysis for the assessment of neurodegenerative diseases: a pattern recognition perspective, IEEE reviews in biomedical engineering 12 (2018) 209–220.

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

[12] M. Gil-Martín, J. M. Montero, R. San-Segundo, Parkinson's disease detection from drawing movements using convolutional neural networks, Electronics 8 (8) (2019) 907.

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

[14] S. Chakraborty, S. Aich, E. Han, J. Park, H.-C. 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), IEEE, 2020, pp. 298–303.

[15] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, Advances in neural information processing systems 25 (2012) 1097–1105.

[16] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, arXiv preprint arXiv:1409.1556.

[17] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[18] S. J. Pan, Q. Yang, A survey on transfer learning, IEEE Transactions on knowledge and data engineering 22 (10) (2009) 1345–1359.

[19] C. Tan, F. Sun, T. Kong, W. Zhang, C. e. a. Yang, A survey on deep transfer learning, in: International conference on artificial neural networks, Springer, 2018, pp. 270–279.

[20] Y.-P. Lin, T.-P. Jung, Improving eeg-based emotion classification using conditional transfer learning, Frontiers in human neuroscience 11 (2017) 334.

[21] D.D.J.S., A comprehensive hands-on guide to transfer learning with real-world applications in deep learning, accessed: 15 September 2020.
URL `https://towardsdatascience.com`

[22] P. Marcelino, Transfer learning from pre-trained models, accessed: 15 September 2020.
URL `https://towardsdatascience.com`

[23] K. Mader, Parkinson's drawings, available at, accessed: 7 August 2020.
URL `https://www.kaggle.com/kmader/parkinsons-drawings`

[24] T. Zhang, C. Y. Suen, A fast parallel algorithm for thinning digital patterns, Communications of the ACM 27 (3) (1984) 236–239.