Deep Analysis of Handwritten Notes for Early Diagnosis of Neurological Disorders

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***Abstract*—Parkinson's is not just an older person's disease. Although, it is typically diagnosed around the age of 60 or later, however, usually the symptoms of Parkinson's may start at 50 years old or even earlier. Usually, the symptoms of Parkinson's appears when approximately 70% of the dopamine-producing cells have stopped working normally. Evidence suggests that early diagnosis of Parkinson's disease leads to an effective path to manage its symptoms efficiently. However, the diagnosis of Parkinson's is challenging, especially in its early stage. Handwriting abnormalities are majorly used for diagnosis of Parkinson's disease (PD) have handwriting abnormalities. Selecting a writing task can affect the diagnosis performance. In this paper, we analyzed different writing task for Parkinson patient to select an optimal writing task that could help to improve the diagnosis performance. We have used transfer learning based strategies and used different methods to select an optimal writing task. Extensive evaluation of different writing styles showed that complex task are much better in diagnosis of Parkinson disease in comparison to simple task, however, further research is warranted to gain better insight into analysis of complex task.**

***Index Terms*—Parkinson's, Early detection, Brain disorder, Handwriting, Micrographia, Neurological Disorders.**

I. Introduction

Parkinson's is the central nervous system disorder that leads the patient to shaking, stiffness, and difficulty in balance, walking as well as coordination. It damages the nerve cells (cells of the basal ganglia and the substantia nigra) in the brain that produces dopamine which is required to control the muscles and their movement. It affect about 50% more men than women. The cause of Parkinson's is still unknown however, medical experts believe that symptoms are due to the chemical imbalance in brain and there is no cure so far. Parkinson's, disease a chronic disease that usually begin gradually and worsens over time. Each year 50,000 new cases are reported only in United States and there are more than 10 million Parkinson patient world wide and. This number could be even bigger, since Parkinson's is often misdiagnosed. Overtime, Parkinson disease slow down the movement resulting dependency in performing simple task. Thus, it is one of the costly disease with burden of approximately $23,000 per patient.

Handwriting could be a profoundly skilled and complex facilitated engine activity. Writing a sentence requires the energetic transaction of the lower arm, wrist, and finger muscles [1]. It has been well archived that penmanship is influenced in Parkinson's infection (PD) and micrographia happens in around 63% of PD patients as an early motor feature [2]. The larger part of patients with Parkinson's infection (PD) have penmanship abnormalities. Micrographia (abnormally little letter measure) is the foremost commonly reported and effortlessly detectable handwriting abnormality in patients with PD. A sudden change in the size of handwriting may be an early indicator of Parkinson's disease. People with PD have a hard time controlling movement because of the changes in the brain. This can make fine motor skills like writing more difficult. Micrographia is the medical term for "small handwriting." Parkinson's patients often have handwriting that looks cramped. Individual letters tend to be smaller than normal, and words are spaced closely. A person with PD may begin writing a letter in their regular handwriting but gradually start writing in smaller font.

Currently, the diagnosis is based on the assessment of several tasks such facial expression difficulties [3], [4], writing [5]–[7] or drawing [8], walking [9]–[11] and speaking [12], [13] by Parkinson's patient. Parkinson's using handwriting is a successful strategy as compare to neurological testing and brain scanning because of their costly and time-taking nature [7], [14], [15]. Moetesum et al. [16] used the Fusion techniques (early fusion and late fusion) in order to improve classification. They assessed the visual properties of handwriting for determination of Parkinson's infection. Author used the Pahaw dataset proposed by Drotar et al. [17], [18]. Pahaw dataset was captured using 75 subjects but some of the subjects not completed the task successfully so there samples were ignored. In their study they use 72 subjects (36 PD and 36 control). CNN along with the SVM classifier is used for the recognition of PD and got 83% accuracy. Later on, Naseer et al. [5] used the Pahaw dataset with Imagenet and MNIST dataset. They performed the information increase methods in arrange to extend the estimate of the dataset such as turns, horizontal and vertical mirror images, sharp images of the PaHaw dataset. For the MNIST dataset they performed resize and the channelization. They classify these dataset using deep convolutional neural network classier using fine-tune approach. They have divided the dataset into two parts in which 90% of the dataset is reserved for the training purpose and remaining 10% of the dataset is reserved for testing purpose. They extract the visual patterns and got a recognition rate of 98.28% using AlexNet architecture of CNN on ImageNet dataset as source domain and PaHaW dataset as destination domain. Afonso et al. [19] proposed an application of recurrence plot to map the signals which are than fed to the convolutional neural network for learning appropriate data. They used HandPD dataset using the same splits and image resolution as the Pereira et al. [20] performed. However, due to unavailability of Parkinson handwritten data as well as huge variation in symptoms of Parkinson's disease, both traditiaonal machine learning and deep learning based methods are struggling to achieve good accuracy [14], [21]. The process of selecting source for transfer learning and transferring the pre-learnt knowledge is referred as fine-tuning. In this paper, we performed Parkinson's identification using handwriting using deep transfer learning based techniques. Extensive experimental analysis shows that proposed approach considerably improves the diagnostic performance as compared to state of the art anomaly detection methods.

The **key contributions** of this work are illustrated as follows:

- We analyzed different handwritten tasks to investigate the behavior of Parkinson patient and impact of different writing task on identification of Parkinson disease.
- In order to generalize, we have performed experiment using several deep learning models and utilized pre-trained knowledge to classify different handwritten task performed by Parkinson patient.
- We investigate different handwritten task performed by Parkinson's patient and select an optimal task that could be used for better identification of Parkinson's patient in comparison to other writing styles.
- In order to improving the overall classification performance and to achieve the effective results for early identification, the input space has been increased using different combined datasets' samples.

Rest of the paper is organized as: in the next section, we analyzed different handwriting task using deep transfer learning followed by handwritten Parkinson's datasets. In section IV, we performed extensive experiments, evaluate and compare the results with state-of-the-art methods, followed by observation and future recommendation. Finally, conclusion is drawn in section VI.

II. Deep Analysis of Handwritten Notes

The objectives of this work is to perform the kinematic analysis of different handwriting task performed by Parkinson patient and observe the different complexities during handwriting task with future direction of research in the early diagnosis of Parkinson patient. To conduct a thorough analysis for Parkinson's diagnostic recognition, we made reference to the four most commonly used architectures in this domain, namely AlexNet, [22] GoogleNet [23] , VGGNet [24] , and ResNet [25] for evaluating both original datasets for the four Parkinson's recognition tasks. In first case, we performed experiment by exchanging the weights of the pre-trained network utilizing source dataset (ImageNet) to a network utilizing target datasets (PaHaW, HandPD, NewHandPD, and Parkinson's drawing dataset). we describe four Parkinson's datasets which are used in the experiments.

TABLE I
Summary of the CNN Models

CNN Models	Layers	Parameters
AlexNet	8	60 M
GoogleNet	22	102 M
VGGNet-16	16	138 M
VGGNet-19	19	144 M
ResNet-50	50	25.6 M
ResNet-101	101	44.5 M

In addition to fine-tuning, we have used the weights inferred from training the network on the source dataset namely, ImageNet and utilizing the outputs from the intermediate hidden layer (like edges and blobs) as features for training a linear classifier on the data of target datasets namely, PaHaW, HandPD, NewHandPD and Parkinson's Drawing dataset. This is called freeze strategy of transfer learning. The network builds a progressive representation of input images. We conducted number of experiments to explore which layer outperforms in the extraction of features and conclude that the more profound layers contain higher-level highlights, built utilizing the lower-level highlights of prior layers. To get the feature representations of the training and test images, we use activation on the fully associated layers of the six pretrained networks. In our whole framework, we use two different image resolution 227 x 227 for AlexNet while 224 x 224 for the other five pretrained architectures. We investigate all early featured layers of each model but the fully connected layers give salients features. Therefore, we use completely associated (fc) layers from which the highlights can be determined. The layers are named as fc6, fc7 in AlexNet and vgg16/19, loss3-classifier in GoogleNet, fc1000 in ResNet50/101 netwoks respectively.

III. Datasets

Occurrence of kinetic/postural tremor is one of the key indication of Parkinson disease. It occurs due to the change in functionality of neuronal mechanism in patient having Parkinson symptoms, thus patient always face difficult in performing the task that are motor dependent such as walking, writing, speaking. Handwriting is one of the earliest symptoms that can be notices and can be used to diagnose the Parkinson disease i.e. sudden change in size of handwritten text is considered as an early indicator. Handwritten notes assessment for early diagnosis has been actively used by clinicians. To develop an automated Parkinson identification several handwritten dataset has been developed. In this study, we will analyzed different task of four different handwritten datasets (PaHaW dataset[1], HandPD dataset[2], NewHandPD dataset and Parkinson's Drawing Dataset[3]) to differentiate Parkinson's patient from healthy.

[1]https://bdalab.utko.feec.vutbr.cz/
[2]http://wwwp.fc.unesp.br/ papa/pub/datasets/Handpd/
[3]https://www.kaggle.com/kmader/parkinsons-drawings

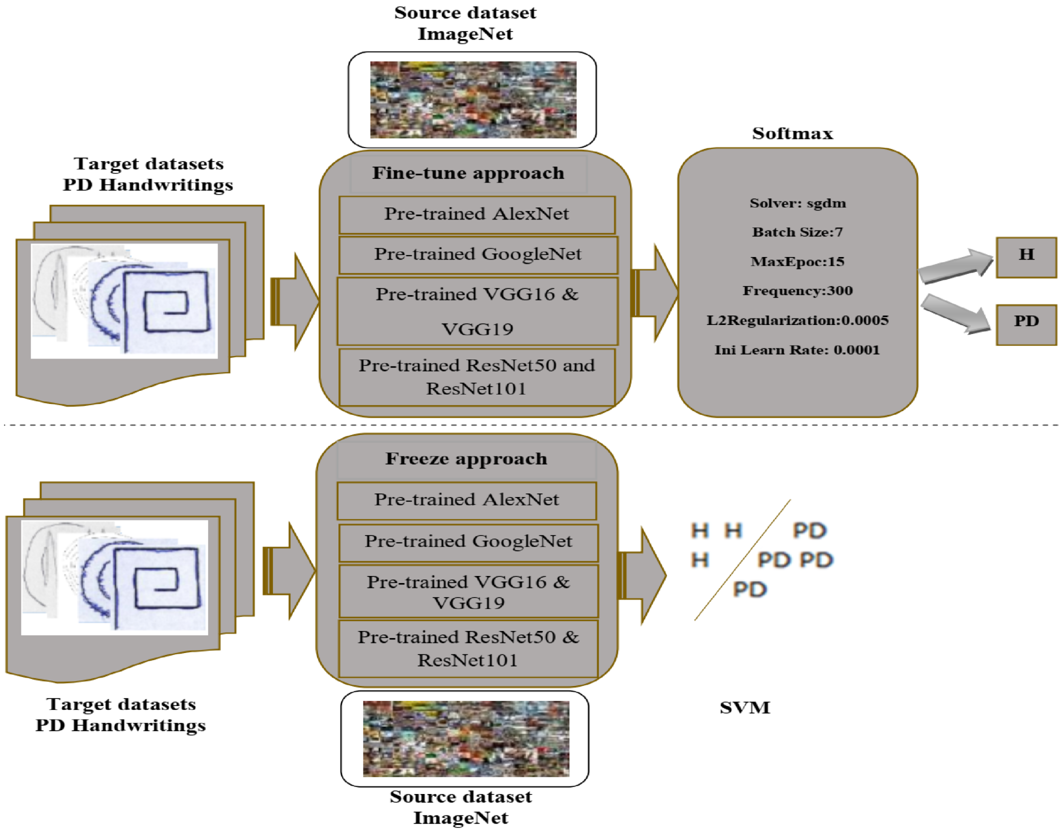

Fig. 1. Proposed Parkinson Diagnosis

PaHaW dataset is collected using digitizing tablets from 75 subjects (37/38 Parkinson's/healthy subjects) while preforming multiple handwriting task [17], [18]. Each subject is asked to complete eight handwriting tasks like spiral drawing, "l", "le", "les", "lektorka", "porovnat", "nepopadnout" and "Tramvaj dnes uz nepo-jede". In comparison to PaHaW, HandPD dataset is fairly large dataset that consists of 92 subjects (74/18 Parkinson's/healthy subjects) [26][4] acquired while performing complex task spiral and meander task. HandPD consist of 736 images (spiral 368 and meander 368). Similar to HandPD, the NewHandPD dataset consists of 66 individuals in which 31 are Parkinson's patients and 35 are healthy individuals [27][5]. NewHandPD dataset are collected while performing four different tasks such as circle, spiral, meander and signals. Each individual asked to write 1 data of circle, 4 data of meander and spiral, and also to record 12 samples of signals. There are 394 images and 792 signals. In this paper, we evaluate our proposed study using images data.. In addition to PaHaw, HandPD and NewHandPD, we have used handwriting dataset to see behaviour of Parkinson patient while performing drawing. Parkinson's drawings dataset consists of handwriting samples[6]. Dataset consists of training and testing groups having two different types of image representations [28]. . Parkinson's drawing dataset consists of 204 images in which 102 is of spiral and the remaining images are of wave.

[4]http://wwwp.fc.unesp.br/ papa/pub/datasets/Handpd/
[5]http://wwwp.fc.unesp.br/ papa/pub/datasets/Handpd/
[6]https://www.kaggle.com/kmader/parkinsons-drawings

IV. Results and Discussion

If Parkinson disease is diagnosed early, a course of treatment is started which could reduce the progression of disease. However, each person has different symptoms, disease progression, lifestyle and physical tolerances, i.e., two people with Parkinson's disease will unlikely experience the condition the same way. There exist high variability in the Parkinson's symptoms, which make it challenging to achieve high accuracy with high sensitivity. In this section, we performed series of experiments in number of round using different CNNs architectures on different handwritten task to analyze analyse the handwriting dynamics of Parkinson's patient. We performed 10-fold cross validation and compare the performance of our best network with state of the art methods.

Table II and Table IV show the experimental results on different handwritten task. We can notice that complex task such as Meander and Spiral showed considerably better performance as compared to simpler tasks. To further investigate the performance of transfer learning using different handwritten drawing samples, we have adapted two approaches of deep transfer learning to thoroughly explore the effectiveness of handwritten task or combination of handwritten samples in

TABLE II
AVERAGE ACCURACY OF EACH SAMPLE AND COMBINATION OF SAMPLES OF FOUR PARKINSON'S DATASETS USING FINE-TUNE APPROACH OVER THE TEST SET.

Round	Samples	AlexNet	GoogLeNet	VGG16	VGG19	ResNet50	ResNet101
Round1	Spiral (PaHaW)	**62.50**	37.50	**62.50**	50	37.50	50
Round2	Spiral (HandPD)	**86.49**	81.08	81.08	62.50	81.08	81.08
Round3	Meander (HandPD)	**89.19**	83.78	**89.19**	**89.19**	81.08	81.08
Round4	Spiral + Meander (HandPD)	84.93	83.56	**90.41**	82.19	84.93	80.83
Round5	Circle (NewHandPD)	**83.33**	66.67	66.67	83.32	83.32	**83.33**
Round6	Spiral (NewHandPD)	84.62	84.62	**88.46**	**88.46**	**88.46**	69.23
Round7	Meander (NewHandPD)	**92.31**	88.46	84.62	80.77	84.62	76.92
Round8	Spiral + Meander (NewHandPD)	97.37	90.91	97.73	**98.11**	97.73	84.09
Round9	Circle + Spiral + Meander (NewHandPD)	84.75	84.75	88.14	81.36	**98.31**	71.19
Round10	Spiral (Parkinson's Drawing)	60	60	**90**	80	80	70
Round11	Waves (Parkinson's Drawing)	80.00	80.00	70	80	**90**	50
Round12	Spiral+Waves	70	**90**	75	75	80	55
Round13	PaHaW + HandPD + NewHandPD + Parkinsons's Drawing	**90.12**	81.48	80.25	77.78	88.89	79.01
Round14	HandPD, NewHandPD & Parkinsons's Drawing	90.85	95.42	**96.08**	95.42	90.20	90.85

identification of Parkinson's. Table IV shows the handwritten samples of four benchmark datasets. We can observe form extensive experiments, that the freeze approach of transfer learning showed considerably better performance than finetune approach in terms of both accuracy as well as computational complexity. We have achieved the highest a classification and identification rate of 98.31% using ResNet50 with freeze approach (experiment 9). We can summarize the above discussion and experimental results as (i) complex tasks such as handwritten circle, Meander and spiral drawings are the good bio-marker for early PD identification and freeze based transfer learning are better than finetune for Parkinson diagnosis. Furthermore, we have performed experiments with different network size. We noticed that smaller network showed much better performance in comparison to larger network. This may be due to the one-class problem or small dataset size, i.e. network has learnt the handwritten sample well, but it has not learnt enough to generalize to variations.

Table V shows the comparison of diverse Parkinson's disease classification. An important comparison of our framework is possible with works of Naseer et al. [5] Pereira et al. [20], [29] and [8], Afonso et al. [19] and Moetesum et al. [16]. Handcrafted features showed poor performance 78.9% recognition rate on task of spirals and meanders [30]. Recently, deep learning has been used and showed considerable improvement over traditional machine learning methods. Pereira et al. used convolutional neural network and meta-heuristic methods on HandPD dataset and achieved 80.19% and 90.38% recognition rate respectively [20], [29]. Pereira et al. [8] presented time series based deep convolutional neural network that showed considerable improvement in performance 93.50%. In comparison with Pereira et al. [20], [29] and Naseer et al. [5], our system appeared impressive pick up in execution, i.e., 80.19% [20], 90.38% [29], 98.28% [5] to 98.31% using ResNet50 with freeze features .

V. OBSERVATION AND FUTURE RECOMMENDATION

In this work, we have the following key observation

- We observe that complex handwritten tasks such as meander, spiral and wave can be better task to identify early Parkinson's accurately as these are difficult to perform for Parkinson's patient.
- Results showed that transferring the learnt knowledge help to improve the diagnostic performance.
- In comparison to other biomarkers, complex task based handwriting based identification have future potential as cost-effective, fast and reliable biomarker.

Based on our extensive evaluation, we suggest the following recommendation that should be considered in future research

- Results showed that complex handwritten tasks such as meander, spiral and wave considerably outperform simpler task, thus, we suggest to collect complex task dataset that can not only help to identify the Parkinson patient but also help to describe the severeness of disease.
- We think that the identification performance can be improved by utilizing the additional clinical information such as age, gender etc.

VI. CONCLUSION

There is no cure of Parkinson disease, however, affect of disease can be reduced by management plans. Thus, early diagnosis is very important because treatments such as levodopa/carbidopa (levodopa-carbidopa intestinal gel (LCIG) used for treatment of motor fluctuations in patients with advanced Parkinson's disease are more effective when administered early on in the disease. In order to develop early diagnostic system, we did comprehensive study of different handwritten task to select an optimal handwritten task. In conclusion, we found that complex handwritten tasks (such

TABLE III
AVERAGE ACCURACY OF EACH SAMPLE AND COMBINATION OF SAMPLES OF FOUR PARKINSON'S DATASETS USING FREEZE APPROACH OVER TEST SET

Rounds	Samples (Dataset)	AlexNet		GoogLeNet	VGG16		VGG19		ResNet50	ResNet101
–	–	fc6	fc7	loss3-classifier	fc6	fc7	fc6	fc7	fc1000	fc1000
Round1	Spiral (PaHaW)	**75**	**75**	**75**	37.50	62.50	**75**	62.50	37.50	37.50
Round2	Spiral (HandPD)	**97.30**	89.19	75.68	94.59	94.59	91.89	91.89	**97.30**	97.3
Round3	Meander (HandPD)	83.78	86.49	86.49	91.89	94.59	91.89	91.89	91.89	**97.30**
Round4	Spiral + Meander (HandPD)	91.78	91.78	89.04	<u>**98.04**</u>	90.41	87.67	89.04	93.15	93.15
Round5	Circle (NewHandPD)	83.33	83.33	83.33	83.33	83.33	83.33	83.33	83;2.33	83.33
Round6	Spiral (NewHandPD)	92.31	**96.15**	**96.15**	92.31	92.31	92.31	**96.15**	80.77	92.31
Round7	Meander (NewHandPD)	92.31	**96.15**	73.08	88.46	88.46	92.31	92.31	92.31	88.46
Round8	Spiral + Meander (NewHandPD)	92.45	94.34	88.68	92.45	84.91	**96.23**	90.57	88.68	**96.23**
Round9	Circle + Spiral + Meander (NewHandPD)	93.22	93.22	88.14	89.83	89.12	89.83	94.92	**96.61**	**96.61**
Round10	Spiral (Parkinson's Drawing)	**92.16**	90.00	90.00	90	90	90	80	90	80
Round11	Waves (Parkinson's Drawing)	80	**90**	80	80	80	80	80	70	70
Round12	Spiral+Waves	**95**	85.00	80	90	90	80	80	85	75
Round13	PaHaW + HandPD + NewHandPD + Parkinsons's Drawing	91.30	88.20	88.20	88.20	88.20	90.06	**91.93**	86.34	88.82
Round14	HandPD, NewHandPD & Parkinsons's Drawing	92.16	85.62	88.89	90.20	87.58	92.81	**93.46**	**93.46**	92.81

as meander, spiral and wave) can help to diagnose Parkinson disease efficiently in comparison to simpler task. Thus, we suggest to collect complex task dataset that can not only help to identify the Parkinson patient but also help to describe the severeness of disease. We think that the identification performance can be improved by utilizing the additional clinical information such as age, gender etc. Thus, future research should also focus on development of dataset consist of clinical features and complex handwritten task.

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TABLE IV
Analysis of Different Handwritten Samples for Parkinson's Disease Identification

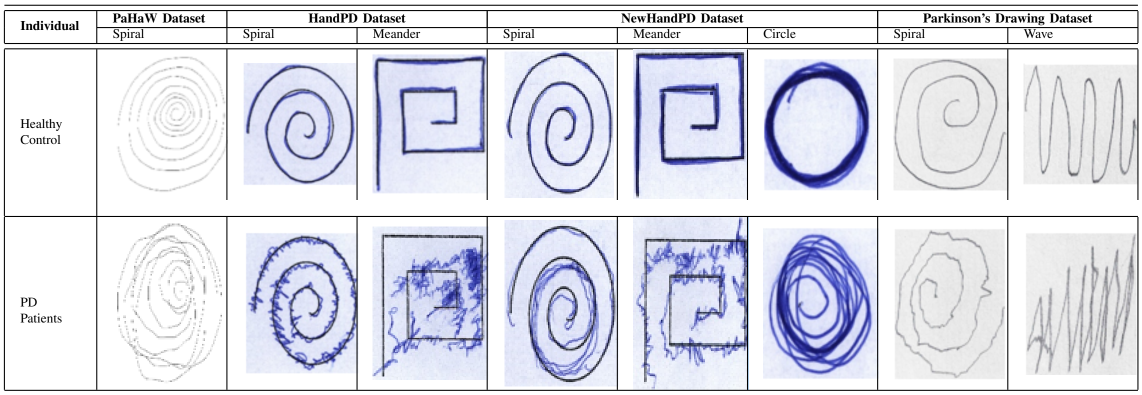

TABLE V
COMPARISON OF AVERAGE OVERALL ACCURACY OF PROPOSED SYSTEM WITH AVAILABLE SYSTEMS IN THE LITERATURE

System	Samples	Dataset	Results
pereira et al. [30]	Spirals & meanders	HandPD	78.9%
pereira et al. [20]	Meander Spiral	HandPD	87.14% 80.19%
pereira et al. [29]	Spiral	HandPD	90.38%
Pereira et al. [8]	Circle, Spiral, MEander, Clock and anti-clock arrows	NewHandPD	95%
Moetesum et al. [16]	letters, words, textlines, & Spiral	PaHaw	83%
Naseer et al. [5]	Spiral	PaHaW	98.28%
Proposed	Circle, Spiral & Meander	NewHandPD, Parkinson's Drawing	98.31%

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