Refining Parkinson's Neurological Disorder Identification Through Deep Transfer Learning

Amina Naseer, Monail Rani, Saeeda Naz, Muhammad I Razzak, Muhammad Imran, and Guandong Xu

Abstract—**Parkinson's disease (PD), a multi-system neurodegenerative disorder which affects the brain slowly, is characterized by symptoms such as muscle stiffness, tremor in the limbs and impaired balance, all of which tend to worsen with the passage of time. Available treatments target its symptoms, aiming to improve the quality of life, however, automatic diagnosis at early stages is still a challenging medicine-related task to date, since a patient may have an identical behavior to that of a healthy individual at the very early stage of the disease. Parkinson's disease detection through handwriting data is a significant classification problem for identification of PD at the infancy stage. In this paper, a PD identification is realized with help of handwriting images that helps as one of the earliest indicators for PD. For this purpose, we proposed a deep convolutional neural network classifier with transfer learning and data augmentation techniques to improve the identification. Two approaches like freeze and fine-tuning of transfer learning are investigated using ImageNet and MNIST dataset as source task independently. A trained network achieved 98.28% accuracy using fine-tuning based approach using ImageNet and PaHaW dataset. Experimental results on benchmark dataset reveal that proposed approach provides better detection of Parkinson's disease as compared to state of the art work.**

Keywords: Parkinson disease, handwriting analysis, neurodegenerative disorder

1. Introduction

Walking into the bedroom, using technology gadgets, washing dishes, reading newspaper, writing or typing text etc. all of these daily based actions involve movement. We never noticed that how brain works, we never think twice about the certain action before performing it, that goes into brain and makes the movement possible, however, some of us suffer this issue i.e. movement disorder may be possible in case ones process go awry due something happens to brains deep parts basal ganglia and the substantia nigra and you lose control over the motor system. Deficiency results in change in speech and movement, depression and anxiety. Parkinsons disease is the best known movement disorder.

Worryingly the global prevalence of Parkinson Disease (PD) is increasing over time. Currently, about 1 million Americans and 10 million people world wide suffer from Parkinson's, a progressive neurological disorder according to APDA (American Parkinson Disease Association) [1]. Famous patients-turned-advocates include Muhammad Ali, Michael J. Fox and Janet Reno. It is expected to double within the next 20 years (up to 2% and 6% in people over the age of 60 and 80 years respectively). Currently, the cure for Parkinson disease is not available, and the therapies can only help to control motor symptoms by reversing the DA deficiency [2]. Furthermore, there's no single test for Parkinson's diagnosis, moreover, there is no clear indication of what causes Parkinson, although physician technically understand what happens with the patient. Unlike other disease diagnosis, genetic models even do not generate important cardinal features of PD [2, 3]. However, there are traditional aproaches for diagnosis and investigation of PD which are invasive methods like Computed tomography (CT) scan, MRI, X-rays, PET, SPECT ("Single Photon Emission Computerized Tomography") / DAT ("Dopamine Transporter") scan, ultrasound, etc which are costly and can be effective when disease is spread over the brain. We require non-invasive and clinical screening test to diagnose PD at an early stage and assist the physician to cure and avoid the spreading of the Parkinson's disease in other cells of the brain.

Recently, several machine based systems have been proposed to identify the early symptoms of Parkinsons and similar neurological diseases and different mode of input has been used such as voice, handwritten, speech patterns to observe subtle. Furthermore, muscular movements devices such as wearable sensors as also been used for PD identification. Among Parkinsons Disease (PD) motor symptoms, freezing of gait

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(FOG) may be the most incapacitating. Aside from the primary motor symptoms, difficulties starts to occur frequently in handwriting of patient i.e. a major complaint of patients with PD is their inability to sign legibly.This phenomena is generally known as micrographia (abnormally small, cramped handwriting or the progression to progressively smaller handwriting) and considered as a biomarker for detection of Parkinson's disease i.e. researches have revealed that about 63 percent of Parkinson's patients have suffered from micrographia [4]. It is the one the most commonly reported and easily detectable handwriting abnormality in patients with PD. However, micrographia is perhaps the tip of the iceberg representing the handwriting abnormalities in PD [5]. Studies have shown that there is a strong evidences of correlation between handwriting changes and problems in the nervous system [6–9]. The symptoms of handwriting impairment in Parkinsons patients are less handwriting speed, low pressure, velocity, less continuity as compared to healthy ones. So handwriting analysis is an efficient approach for detection of disease as compare to neurological testing and brain scanning as these methods are expensive and machinery depended. There is no medication or cure is available to stop the progression and spreading of Parkinson's disease. Although, it is possible to stop or decrease the PD at earlier or infancy stages. But at later stages, when the disease has gone to be worst then an alternative solution is surgical treatment. However, for safety and cure the quality of patients brain cells, detection of Parkinsons disease at an earlier stage is necessary but clinical diagnosis are expensive, leads to inaccurate results and inadequate services to patients.

Over the period of time, a substantial number of studies based on handwriting have been presented and shown a product of perceptive, cognitive and fine motor skills that can also be employed as an effective tool for early diagnosis of PD [10–12]. Even though many clinical examinations as well as automatic diagnosis approaches PD have been proposed, it is still very important that we should exert more effort in automating its diagnosis efficiently. The paradigm-shifting results delivered by CNNs were in part accomplished with the help of extremely large training datasets, which is unrealistic Parkisons's identification due to availability of small data size, as a results, direct application of CNN could not be effective. In addition to the relatively small sample size, the other important limitation of most of the studies are focused on hand crafted features due to limitation of deep learning methods on small dataset, however, automatic extraction of features could helps to increase the identification performance [13]. Deep learning methods have demonstrated tremendous success in a variety of applications in various fields [14–19], however, it is data hungry approach and requires atleast 10 times the degree of freedom that can often preclude the use of CNNs for applications where dataset can be challenging. In order to address the problem of limited training data, transfer learning could be used to tune the already grained storing knowledge on similar problem. To overcome these challenges, in this paper, we plan to investigate the extendability of the trained CNN classifier on ImageNet and MNIST via transfer learning on target dataset named as PaHaW datset. The objective of this work is to perform an extensive experiment using Convolutional Neural Network (CNN) and the concept of transfer learning due to limited and finite samples of PaHaW Dataset collected from patients having PD and healthy persons, respectively. AlexNet is the relatively simple type of CNN architecture has got great interest and success in different pattern recognition and classification tasks.

In the literature, AlexNet has been proven as an excellent deep leaner for the various problem in different domains. Therefore, we explore the two common approaches of transfer leaning i.e., freeze and fine-tuning. In each approach, we conduct two studies. The first study uses pre-trained AlexNet on ImageNet dataset (natural images) and second study implement AlexNet form scratch on MNIST dataset (handwriting digits) as a source task for extraction of features for transferring to the target task PaaW datset. Each study has series of experiments for investigation of ways of features extraction like AlexNet-freeze and AlexNet-finetune due to limited samples of PaHaW dataset in the next sections.

The key contributions of this studies are :

- Development of early Parkinson's diagnosis using transfer learning and data augmentation techniques due to the limitation of handwritten data of Parkinson's patient.
- Find out the increase in the input raw samples using data-augmentation and other prepossessing techniques result in increasing the accuracy of deep CNN.
- Investigate that how the visual patterns of natural images (ImageNet dataset) and handwrittn digit images (MNIST dataset) can be benefitial in identification of PD.
- Explore that how features learned from one large dataset using freeze features and fine-tuning approaches of transfer learning can improve the recognition in other domain.
- This study analyze, evaluate and compare two different data sources for transfer learning for Parkinson's disease identification.

Rest of the paper is organized as follows. Section 2 demonstrates the concept of deep neural network and transfer learning in details. Section 3 presents the overview of related work regarding the deep and transferring based approaches for PD's identification. Section 4 describes the proposed methodology for Parkinson's diagnosis. Section 5 details the experimental results along with comparison with state-of-the-

art work. Finally conclusion and future directions are discussed in Section 6.

2. Related Work

Ever since difficulties in handwriting were first reported by James Parkinson in patients with the shaking palsy, described as "the hand failing to answer with exactness to the dictates of the will". Earliest identification was based on paper based handwritten text of selected patient with significant observable micrographia [20]. Since then, Parkinson's disease identification an active area of research in the pattern recognition community for over four decades now. With the development of hand-held devices and digitizing tablet, the collection of handwriting samples using digitizing tablets is easy, non invasive and contains additional information (such as speed, pressure etc.) that paper based does not.

Until now, machine-learning based approaches are considered as supportive, and not substitutive of human in making the clinical decision. Unlike other machine learning applications, there are still some barriers to the complete translation in health industry. Recently, several attempts have been made to design decision support systems for differential diagnosis of PD in recent years. These includes speech assessment [21–27], gait monitoring [28–32] or tremor assessment [33, 34]. There are several challenges involved in these methods i.e. speech assessment requires high quality noise free recording conditions, gait monitoring and tremor assessment requires specialized equipment such as accelerometers or gyroscopes. Whereas, handwriting based diagnosis of PD can be easily performed at clinic or even patient's home and does not require any special equipment for data acquisition. Previous studies have proven that there is significant difference between kinematics of PD patients and healthy controls. However extend to which any set of features could be useful in discriminating PD at early stage is still in progress.

Even though many automatic diagnosis approaches PD have been proposed, it is still very important that we should exert more effort in automating its diagnosis efficiently. In order to overcome limitation of conventional models the researchers moved towards deep learner in 2016. Pereira et al. [35] developed an handwriting dataset by capturing images during handwriting task and apply model on pen based features like pressure, tilt and acceleration. Convolutional Neural Network (CNN) was applied with image resolution for classification and achieved overall test set accuracy of 80.19% using ImageNet while considering spiral data. In an other work, Pereir et al. [36] applied CNN for identification of Parkinson's disease. Authors proposed meta-heuristic-based techniques that is Bat Algorithm (BA), Firey Algorithm (FA) and Particle

Swarm Optimization (PSO) in order to fine tune CNN hyper parameters.

Handwriting dataset has been used for detection of Parkinson's disease. CNN gave the effective results on BA approach with over all accuracy of 90.38% for spiral data. Pereira et al. map signals extracted from handwriting dynamics into images.These time series images passed to Convolutional neural network and achieved 93.50% accuracy using feature learned from CCN [37]. Zhang et al [38] applied stacked autoencoders and KNN classifier and employed the speech records and extract the time frequency features such as jitter , shimmer , voice pitch etc and got an accuracy 90.53 % . Grover et al. [39] applied Deep neural network using tensor flow library on voice dataset and yeilded 83.36% accuracy on Motor UPDRS Score and 94.42% accuracy on total UPDRS. Moetesum et al. [40] evaluated the visual attributes of handwriting for diagnosis of Parkinson's disease. Fusion techniques are applied in order to improve classification. For feature extraction applied the convolutional neural network and extracted features are then classify by SVM. Proposed method effectively diagnosed the Parkison's with 83% accuracy. Caliskan et al. [27] proposed Deep neural network classifier for diagnosis of Parkinson's disease on two voice dataset i.e. Oxford Parkinson's Disease Detection (OPD) and Parkinson Speech Dataset with Multiple Types of Sound Recordings (PSD). Authors compared results of deep and conventional models. DNN has the ability to extract hidden features so as increase the classification performance. DNN classified the OPD and PSD dataset with effective accuracy of 93.79% and 68.05% whereas SVM , decision tree and naive Bayes has accuracy of 85.780, 84.371, 69.64%.Eskofier et al. [32] performed the comparison of machine learning and deep learning techniques on IMU (inertial measurement unit sensor) data for detection of Parkinson's disease. CNN effectively classified data with accuracy of 90.0% as compared to AdaBoost.M1 , PART and kNN with accuracy of 86.3, 67.1 and 85.6% respectively. Choi et al. [41] developed an automatic deep learning-based FP CIT SPECT (I-fluoro propyl carbomethoxy iodophenylnortropane single-photon emission computed tomography) interpretation system for diagnosis of Parkinson's disease through images. They applied deep CCN for classification , proposed method have effectively diagnosed the Parkinson's with accuracy of 90.7%. Afonso et al [42] used the different CNN architecture (Imagent,CIFAR-10, LeNet) for classifying the recurrence plot images evaluated from signals of menders and spiral data. By using recursive approach, they have achieved the recognition rate above to 90%. Gupta et al [43] proposed an optimized cuttlefish algorithm (OCFA)for feature selection evaluated it on Parkinson speech with multiple types of sound recordings and Parkinson Handwriting samples datasets. Decision tree and k-nearest neighbor classifier were used on OCFA se-

lected feature that diagnose the Parkinsons disease with an accuracy of 94% approximately. Pereira et al. applied OSCA (optimal crow search algorithm) for feature selection from handwriting dataset and proposed Random Forest, Decision Tree, k-Nearest Neighbor classifier which gave the 100% prediction rate on OSCA selected features [44].

Not only handwritten text, Archimedean Spiral Drawing Test and shape modifications has also been used for Parkinson's diagnosis [28, 45–48]. Deviations from original sample (like loop tightness and width variability, drawing speed and acceleration, frequency and amplitude of oscillations and spiral pressure, etc.) are considered as symptomatic indicators of a disorder. Drotar et al. presented a template consisting of seven different handwriting tasks in addition to conventional spiral drawing task and suggested that the choice of template has significant impact on the performance of the proposed features [49].

TABLE 1: **Summary of deep learning based methods for Parkinsons disease prediction**

Reference	Features	Method	Data Description	Accuracy %
Pereira et al (2016)	pen base features	CNN	Handwriting Data	80.19
Pereir et al (2016)	pen base features	CNN	Handwriting Data	90.38
M Moetesum et al (2017)	automated visual features	CNN	Handwriting Data	83
Caliskan (2017)	automated	DNN	Voice data	93.79 and 68.05
Eskofier (2016)	automated	CNN	IMU Data	90.9
Choi(2017)	automated	CNN	SPECT images	90.7
Pereira (2018)	automated	CNN	handwiting data (time series image)	93.50
Zang (2013)	Time frequency features	DNN with (KNN)	Speech dataset	90.53
Grover (2018)	Voice features	DNN	Voice Data Set	94.42 and 83.36

The current systems are able to achieve about 90% accuracy. However, the unavailability of Parkinsons's patient handwriting datasets and complexity of designing features are the major impediments preventing the research community from mastering this task. On the other-hand, recently deep learning approaches showed tremendous performance to deal such complex task by automatic learning of features as they learns features from raw data to a representation that best describe the data. Deep learning is good to learn visual features from any type of huge data without knowing which feature is important. Deep learning based techniques, however does not perform well on small datasets. It is greedy technique. ImageNet dataset is extensively used for the purpose of transfer learning for many image classification application due to its large size. However, Parkinson's disease dataset consists of handwritten samples, thus, MNIST could be the powerful source for transfer learning as compared to ImageNet. Therefore, In this paper, we are considering MNIST dataset as source dataset for features extraction and later compare with results achieved by networks using ImageNet dataet as a source.

3. Deep Transfer Learning based Parkinson Identification System

In this section, we demonstrate our proposed system using concepts of data augmentation, transfer learning and deep learning on handwriting sample images of Parkinson's patient. Even though, several automatic diagnosis methods for PD have been introduced, still it is very important to exert more effort in automating its diagnosis efficiently. The paradigm-shifting results delivered by CNNs were in part accomplished with the help of extremely large training datasets, however, we do not have enough data of Parkinson's patient. Thus, direct application of CNN could not be effective on hundreds of images gathered by patients. To cope with this challenge, one way is the data augmentation. Number of CNN based networks are trained to investigate the potential of using the pre-trained CNN classifier on ImageNet and MNIST to learn features and then transfer the model on Parkinson's handwritten data. We have divided the proposed methodology into three steps i.e. Data pre-processing and data-augmentation, CNN based features extraction and identification.

Figure 1 shows the general overview of the proposed automated PD detection system using AlexNet with fine tune architecture and freeze architecture for transfer learning.

3.1. Data Preprocessing and Data augmentation

Pre-processing is a key step in pattern recognition and machine learning. Different techniques like binarization, transformation, image enhancement, sampling, normalization, data augmentation or noise removal etc. are the main techniques of preprocessing step that apply on raw data. As CNN directly works on raw data, thus, it needs to be refined before training to reduce the variations and noisy pattern. We conducted studies using PaHaw dataset having handwritten text written by PD's patients and healthy person. The original dataset has number of online attributes like x,y coordinate, pen status (touching surface of paper
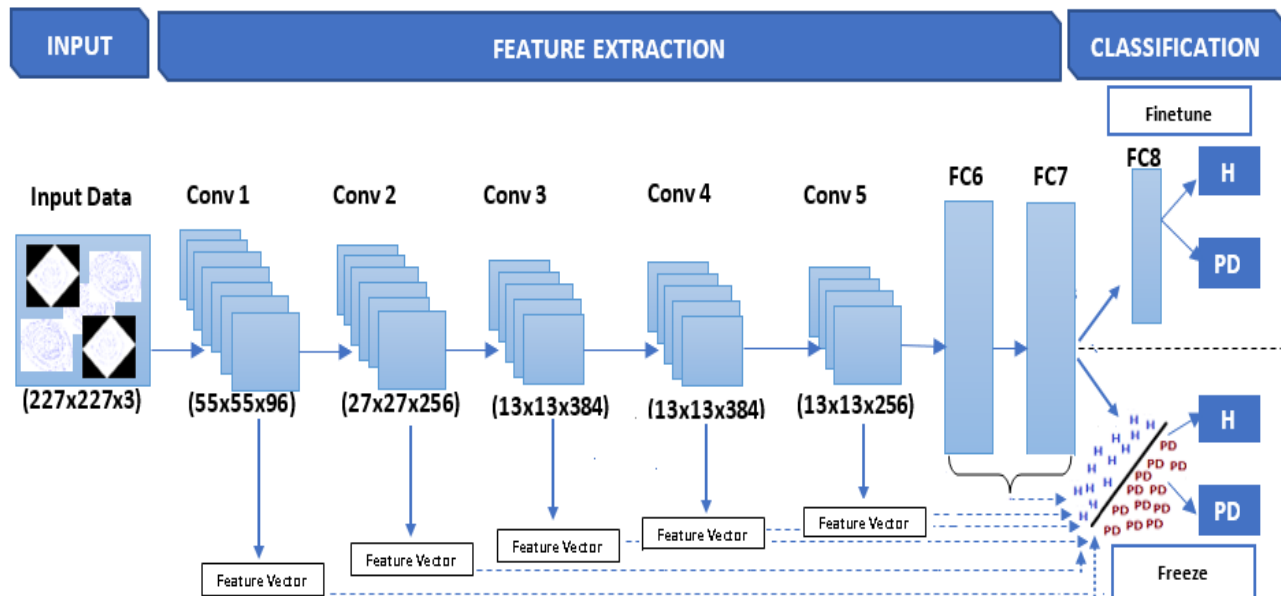
Figure 1: Overview of Proposed System for Parkinson's Disease Detection using AlexNet-Finetune and AlexNet-Freeze

or not), pressure etc. We first plot the image using these information as shown in Figure.2.a. The handwritten text consist of several irrelevant information that could affect the accuracy of diagnosis i.e., PaHaW data contain values of in-air as well as on surface movement. We have removed the in-air movement values from images. Figure.2.b depicts the removal of in-air movement. We can observe from the data that the handwritten text consist of extensive amount of noise, thus, we have removed the noise from data first by applying filters such as median filter followed by transferring it into gray scale.

Deep neural networks need large number of instances of images for training the networks, however, in our case, we do not have enough data of Parkinson's patient. Thus, direct application of CNN could not be effective on hundreds of images collect of Parkinson's patients. To cope with this challenge, one way is the data augmentation that can significantly improved the performance of Deep Neural networks. Therefore, we have applied several data-augmentation techniques (rotations, flipping and contours) to increase the the PaHaW training dataset for providing large input space to CNN. In order to reduce over-fitting and increase generalization of network, we deployed data augmentation to collect variety of visual patterns of input raw images as in our case we have small number of handwritten samples from Parkinson's patients. The basic Data augmentation techniques applied in this study like rotation and flipping. The input images are rotated on various angle like angle of 45, 90, 135, 180, 225, 270, 315 and 360. Likewise, input images are

(a) Sample of original image

(b) Pre-processed image
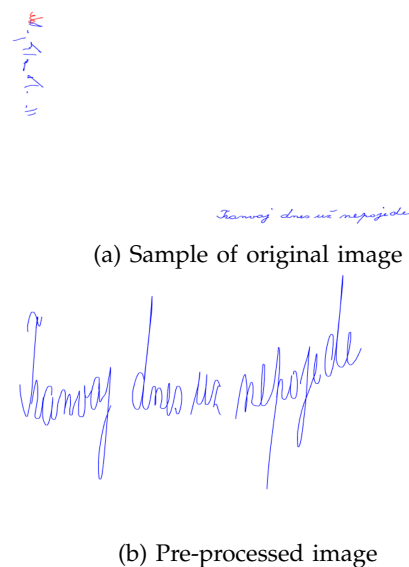
Figure 2: Removal of irrelevant information and white region

horizontally and vertically flipped. As a result, we got 10 variations of one original image using basic techniques of data augmentation. For useful and effective extraction of visual patterns, other techniques are also used for increasing the size. Besides basic data augmentation techniques, we also created contours, high frequency, sharpness of image for expanding the size of dataset. Contours are a single unit thickness of a pattern which help in good features extraction. Con-

tours are computed in the handwritten domains for the effective results. Thus, we computed the contour using $C(x, y) = 255 - Image(x, y)$.

High frequency is computed with the aid of discrete Fourier transform, or DFT. The foundation of the product is the fast Fourier transform (FFT), a method for computing the DFT with reduced execution time. For the input sequence 'x' and its transformed version 'X' (the discrete-time Fourier transform at equally spaced frequencies around the unit circle), the two functions implement the relationships:

$$X(k+1) = \sum_{n=0}^{N-1} x(n+1) W_N^{kn} \tag{1}$$

and

$$x(n+1) = \frac{1}{N} \sum_{k=0}^{N-1} X(k+1) W_N^{-kn} \tag{2}$$

At final step, we use unsharp masking in order to sharp the original image. The sharp image is generated by simply subtracting the image form blurred version of itself as $S_{hp}(x, y) = Image(x, y) - Image_{lp}(x, y)$; where hp is the high pass filter and lp is the low pass filter. The size "N" of PaHaW dataset has increased to "$13xN$" augmented dataset.

In order to train AlexNet on MNSIT (base task) from scratch, we have performed other preprocessing approaches like resizing and channelization of digit images. As an image of MNIST dataset has 28X28 dimension so we have to re-size it on 224X224 dimension according to AlexNet architecture and have to convert from 2D into 3D. It means that we converted gray scale (1 channel) images to RGB (3 channel image) for scratch training of AlexNet architecture then we can use the visual patterns extracted from digits automatically by CNN and transfer to our augmented target task (PaHaW dataset) in classification and identification step.

In next section, the approaches of transfer learning like AlexNet-freeze and AlexNet-finetune are deploying for features extraction form source datasets i.e., ImageNet and MNIST datasets.

3.2. CNN based features extraction

The Convolutional Neural Networks (CNN) are biologically-inspired variants of Multilayer Perceptrons (MLPs) that perform machine learning tasks without requiring any handcrafted feature to be engineered and supplied by the user. Recently, have gained considerable commercial interest due to the development of new variants of CNNs and showed promising performance by advocating the superiority over traditional machine learning algorithms. The main power of a CNN lies in its deep architecture, which allows for extracting a set of discriminating visual features

at multiple levels of abstraction. They have different kinds of layers and each layer works different than other for extraction of visual features. However, one of the biggest limitation is the unavailability of larger and labeled good quality data. The availability of large datasets is rare in the field of healthcare, as data in health industry is very sensitive, expensive confidential and very hard to collect.

Due to insufficient amount of training data, we have implemented pre-trained AlexNet architecture of CNN [50] for extraction of features. In the literature, this technique is known as transfer learning. The visual features are extracted in two ways i.e., a pretrained AlexNet with freeze or fixed approach and pre-trained AlexNet with fine-tune approach. Previous studies have clearly demonstrated that the selection of the source task has an great impact on the performance of CNN on the target task. Recently, ImageNet has been adopted as source for Parkinson's diagnosis [10]. However, MNIST dataset has not explored for features extractions in transfer learning domain for PD identification in the literature. It can provide better performance due to its relevance to the data of PD dataset as both datasets have handwritten text samples.

We deployed the 25 layered Deep Convolutional Neural Network for features extraction and then transfer these features to learn visual patterns from handwriting samples of PaHaW dataset for identification of PD using SVM classifier. AlexNet architecture consists of 5 convolution layers, max-pooling layers, dropout layers, and three fully connected layers. The output of fully connected layer is pass to 1000-way which yields a distribution across 1000 class labels. First convolutional layer filters the $227 \times 227 \times 3$ input images with 96 kernels that have size $11 \times 11 \times 3$ with 4 pixels stride. Second convolutional layer takes the output of first layer (response-normalized and pooled) as an input and filters it with 256 kernels of $5 \times 5 \times 48$ size. Others convolutional layers are connected to each others without any intermediate pooling or normalization layers. Third layer has 384 kernels having $3 \times 3 \times 256$ connected to the normalized and pooled output of second layer whereas fourth layer contains 384 kernels of size $3 \times 3 \times 192$ and fifth layer has 256 kernels of size $3 \times 3 \times 192$. Fully connected layers contains 4096 neurons each. The convolutional layers have more general weights and features which become more specific on fully connected layers. The detailed of AlexNet architecture deployed in our experiments are depicted in Table 3.

The network constructs a hierarchical representation of input images. Deeper layers includes higher-level features, constructed using the lower-level features of earlier layers. Together, the convolutional and down sampling layers serve as feature extractors while the fully connected layers represent a trainable classier similar to a standard multi-layer neural network. In this paper, we conducted two studies
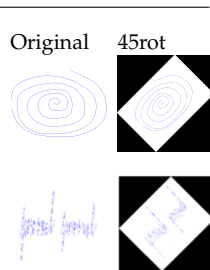
TABLE 2: **AUGMENTATIONNNNn**

Original	45rot

TABLE 3: The detailed AlexNet Architecture used in our Experiments.

Layer	Type	Input	Filter and Size	Stride	Output
Data	Input data	227x227x3	–	—	3x227x227
Conv1	convolution	227x227x3	11×11 and 96	4	$55\times55\times96$
pool1	max pooling	55x55x96	3x3	2	96x27x27
Conv2	convolution	27x27x96	5×5 and 256	2	$27\times27\times256$
pool2	max pooling	27x27x256	3x3	2	256x13x13
Conv3	convolution	13x13x256	3×3 and 384	1	$13\times13\times384$
Conv4	convolution	13x13x384	3×3 and 384	1	$13\times13\times384$
Conv5	convolution	13x13x384	3×3 and 256	1	$13\times13\times256$
pool5	max pooling	13x13x256	3x3	2	256x6x6
Fc6	fully connected	6x6x256	6x6 and	–	4096x1
Fc7	fully connected	4096x1	1x1 and	–	4096x1
Fc8	fully connected	4096x1	1x1 and	–	2x1
Output	fully connected	2X1	–	–	2x1

having two different source dataset. One study explored the effect of visual patterns from ImageNet and another study carried out to investigate the impact of visual patterns extracted from MNIST dataset as the source tasks. The source tasks that the ImageNet dataset consists of 1.2 million images (1000 different classes) in one study and MNIST consists of 0.6 million images (with 10 different classes) in another study for extraction of visual features. The target task is PaHaW dataset having 598 images (75 subject and 2 target classes) for identification of PD. These studies for AlexNet based feature learning, i,e, reusing of freeze or fixed features based approach and fine-tuning the features based approach are demonstrating in the following subsections.

3.2.1. Reusing of Fixed or Freeze Features. We use the weights derived from training the network on the source task (ImageNet and MNIST datasets) and using the outputs from the intermediate hidden layer (like edges and blobs) as features for training a linear classifier on the data of target task (PaHaW dataset). This is called reusing freezing or fixed approach of transfer learning. We have convolutional (conv) and fully connected (fc) layers from which the features can be derived. The layers named as conv1, conv2, conv3, conv4, conv5, fc6 and fc7 in AlexNet's architecture, respectively.

In this study, we carried out series of experiments

that which layer extract best features for our target dataset using tow different source datasets. The different layers of AlexNet are treated as fixed feature vectors extracted using ImageNet or MNIST database independently. Then fed to another linear classifier for classification and identification PD using PaHaW dataset. We conducted number of experiments to explore that which layer outperforms in extraction of features as compare to other. We employed transfer learning by extracting features from different layers like conv1-conv5, fc6, fc7 and fusion of fc6+fc7 of the architecture of AlexNet then fed these features to a dedicated linear classifier i.e. SVM for classification as depicts in Figure 1. The deeper we go into the model, the weights represent more minute and smaller details of an image. Thus, conv1-conv5 show higher level and generic representation of source dataset's images (like edge, blob etc.) while outputs of fc7 represent a more detailed and specific features of the images of source dataset.

TABLE 4: The Dimensions of Features Vectors

Conv1	Conv2	Conv3	Conv4	Conv5	fc6	fc7	fc6+fc7
290400	186624	64896	64896	43264	4096	4096	8,192

3.2.2. Fine-Tuned Features. This technique works by transfering the weights of the pre-trained model using two source dataset (ImageNet or MNIST) to a network

using target dataset (PaHaW). The only exception is the replacement of last fully connected layer of the pre-trained network with new network's fully connected layer. The new last layer has the same number neuron as of the target classes of the target dataset or task. This is called fine tuning approach of transfer learning.

By implementing these technique, we conducted two studies. First, we have employed pre-trained AlexNet for feature extraction using ImageNet dataset (source task), then replaced the last fully connected layer having 1000 neurons from ImageNet with fully connected layer consisting of 2 numbers of neurons from PaHaW dataset (target task).

In second study, experiment carried out using MNIST dataset as a source task and PaHaW dataset as target task. As the last layers of pre-trained AlexNet are configured for 1000 classes of ImageNet datset so we have to replace and fine tune the last fully connected layer of AlexNet architecture to our new problem. We have set the fully connected layer to two classes in our new dataset i.e. Parkinson's Diseases (PD) or healthy (H) for classification and identification purpose as shown in figure 1.

3.3. Classification and Identification

Once the AlexNet trained for Parkinson Disease (PD) learning and classification, then unseen PD and Healthy (H) image(s) in the test set are fed to trained network for identification. The maximum number of epochs are 30. The training network takes 148 iterations per one epoch and total iterations for whole training are 4440. The values of momentum, L2 regularization, initial learn rate and batch size are 0.9, 0.0005, 0.0001 and 7. Total elapsed time is taken upto 10 minutes and 34 second for training a network on fine-tuned based features using ImagNet dataset for PD identification from PaHaW dataset.
The highest recognition rate (98.28%) achieved on spiral pattern using AlexNet-Finetune-ImageNet approach of transfer learning as depicted in Figure. 3. In the subsequent section, a detailed experimental analysis for parameters, patterns and comparative analysis are given with the existing PD identification system in the literature.

4. Experimental Design, Analysis of Results and Discussion

This section aims at presenting the experimental designs and results analysis concerning the CNN-based approach for Parkinsons Disease identification. we evaluate the different parameters for getting the best values of parameters for our experiment, evaluate the CNN networks on different patterns and different approaches (Freeze and Finetune) of transfer learning using ImageNet and MNISt datasets and compare our approach with other state of the art methods [35, 36, 40].

4.1. Study Subjects

We used PaHaW (Parkinson's disease handwriting) database to evaluate our proposed studies. It includes the handwriting samples of 37 Parkinsons patients and 38 healthy subjects, that collected by Droter [49] using digitized tablets. The mean UPDRS-Part V score for PD patients is 2.27 ± 0.84. Each participants asked to perform total eight handwriting tasks but some participants did not completed their task according to given sample, hence, we have excluded their samples. After exclusion, we have 576 samples from 72 (36 PD and 36 control) subjects. The PaHaW is collecting using digitizing tablet, thus it consists of various on-line attributes such as the (x,y) coordinates of the pen trajectory as well as the pen status (whether touching the writing surface or in air) rather than images. We have generated images of the drawing by plotting the normalized (x,y) coordinates corresponding to all positions where the pen is touching the writing surface.

The idea of capturing more information from different samples produced by the same subject was the prime incentive for using PaHaW i.e. dataset consist of different task (tas1-task8) perfromed by same subject. First task contain spiral drawings [51] [52] because it is continuous handwriting sample and it is most suitable for evaluation of movement disorder. Another tasks includes the repeated cursive letter "l" and simple words and a complete sentence. An example of samples of dataset are shown in Figure 4. Description and statistics of data set as illustrated in table 5. The PaHaW dataset is distributed in training and testing set for performance of our proposed methodology.

TABLE 5: **The PaHaW dataset description**

Task	Samples	PD	Healthy	Instances
1	*ArchimedeanSpiral*	36	36	72
2	*Letter 'l'*	37	38	75
3	*Bigram 'le'*	37	38	75
4	*Word 'les'*	37	38	75
5	*Word 'lektorka'*	37	38	75
6	*Word 'porovnat'*	37	38	75
7	*Word 'nepopadnout'*	37	38	75
8	*Sentence*	37	38	75

4.2. Experimental results

Alexnet is trained by varying the options of training parameters to get highest accuracy by training number of networks for our dataset using single Graphics Processor Unit (GPU). We used the implementations provided by the well-known Caffe library7, which is developed under a General-Purpose

Figure 3: The training progress and error rate of the proposed system for Parkinson's disease detection using AlexNet-Finetune-ImageNet approach
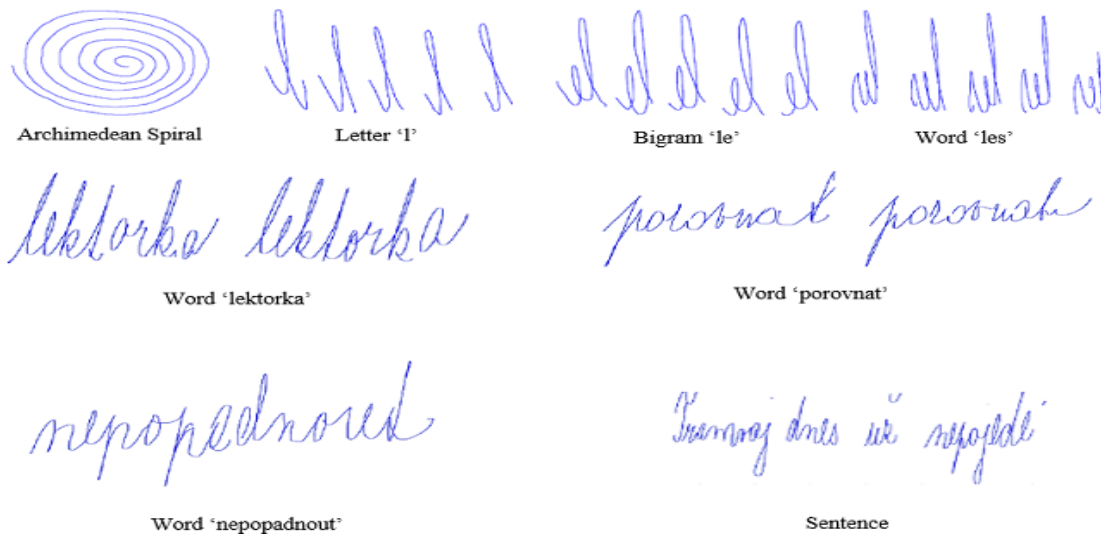

Figure 4: An example of samples of PaHaW dataset

computing on Graphics Processor Units using Single GPU having multiple processor of 2.80 GHz and 2.81 GHz. By default parameters are 0.9 momentum, 128 batch size, 0.0005 L2 regularization, 30 epochs, positive scalar for initial learning rate, 10 learn rate drop period and 0.1 learn rate drop factor. We have conducted number of experiments for evaluation of proposed CNN based system's performance. We kept all default parameters and evaluate the performance of proposed fine-tuned features based system by changing the values of the momentum, Initial Learn Rate, L2 regularization and batch size. The best network achieved

using 0.9 momentum, 0.0005 L2 regularization, 0.0001 initial rate and 7 batch size and got best results upto 98.28%. The best parameter values in our study are shown in Table. 6.

As discussed in earlier section, in this paper, two transfer learning techniques (Freeze and Fine-tuned) are carried out using augmented PaHaW dataset [35] consisting of eight handwritten patterns collected by Parkinson patients and healthy subjects. We have divided the dataset into training set that consist of 90% of samples and testing dataset that consist of 10% samples.

TABLE 6: **Parameters values for fine-tune training the network by using features extracted by CNN**

Parameters	Values													
Momentum	0.9	0.7	0.7	0.7	0.7	0.8	0.9	0.9	0.9	0.9	0.9	0.9	**0.9**	0.9
L2 Regularization	0.0005	0.00005	0.0005	0.0005	0.00005	0.005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	**0.0005**	0.0005
Initial Learn Rate	0.001	0.001	0.0001	0.0001	0.0001	0.1	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	**0.0001**	0.0001
Batch Size	128	128	128	7	128	100	255	200	128	100	64	32	**7**	1
Time (min:sec)	7:23	7:41	7:35	11:38	7:39	7:31	7:53	7:25	7:48	7:31	7:39	7:43	**10:54**	32.10
Accuracy (%)	51.72	65.52	73.28	79.31	53.45	46	92.24	92.24	95.60	95.69	93.10	93.10	**98.28**	50

To explore the performance of Freez based transfer learning, first we explore the performance of AlexNet on different patterns and combined data of PaHaW dataset. Series of eighteen experiments were conducted by fixing conv5 layer using AlexNet-freeze-ImageNet features and AlexNet-freeze-MNIST features, respectively. In the first nine experiments, we investigated and evaluated each and every pattern of PaHaW dataset independently using Alexnet-freeze by fixing the conv5 layer on ImageNet dataset and then other nine series of experiments performed on AlexNet-freeze (conv5) using MNIST dataset. In Table 7, performance of each pattern of PaHaW dataset using fixed conv5 is further demonstrated and compared with both features. Results show that, using AlexNet-freeze-ImageNet, the pattern of spiral drawing (pattern-1) has the highest recognition rate as compare to other patterns. Next higher identification rate is achieved on two short word (pattern-6) are 89.29% and then 79.49% on two letter word (pattern-3) . Similarly, the results are 76.72%,72.32%, 73.21% and 78.99% for patterns-2, patterns-5, patterns-4 and pattern-7 respectively. The proposed pre-trained AlexNet-freeze-ImagenNet network gave 77.48% recognition rate on full sentence (pattern 8), whereas it provided 84.19% identification rate on combined patterns. The evaluation of each pattern using AlexNet-freeze-MNIST features is demonstrated in Table 7. Result shows that pattern of spiral drawing (pattern-1) provided the highest recognition rate of 94.97% as compare to other patterns and the next higher identification rate achieved on sentence (pattern-8) are 86.49% and 86.32% on two letter word (pattern-3) . Similarly, 86.21%, 77.68%, 81.25% and 83.19% for patterns-2,patterns-4,patterns-5 and pattern-7 respectively. The proposed pre-trained AlexNet-freeze-MNIST network provided 68.75% recognition rate on two short word (pattern 6) and overall classification 77.28% on all patterns.

In the second technique (Fine-tuned) of transfer learning, we have also trained eighteen networks using AlexNet-finetune features for different patterns of PaHaW dataset. We conducted two studies to explore either which pattern or combined data show the best performance based on AlexNet-finetune features from sources i.e., ImageNet, MNIST datasets or independently (in last two columns of Table 7). The networks showed promising accuracy for spiral drawing of pattern-1 using fine-tuned features from ImageNet (98.28%) and MNIST (80,17%) as compare to other patterns. The performance of networks are not satisfactory on combined data of all patterns as 84.10% achieved by network trained AlexNet-finetune-ImageNet features and 77.28% accuracy got by network trained on MNIST dataset using fine-tuning approach .

We can conclude from the above discussion that accuracy differ for different pattern using AlexNet-freeze-ImageNet, AlexNet-freeze-MNIST, AlexNet-finetune-ImageNet and AlexNet-finetune-MNIST features. Notice that, all features provided promising result on spiral pattern as compare to others. Spiral images are informative in case of Parkinson's disease detection so we conducted further experiments on spiral pattern. Table 8 depicts the average of ten runs for Parkinson's disease identification rate for the series of experiments having fixed features of con1-conv5, fc6, fc7, fusion of fc6 and fc7 and fine-tuned features using ImageNet dataset as source task and spiral pattern of PaHaW dataset as target task. 93.10%, 93.97%, 94.83%, 96.69% and 98.28% accuracy achieved using conv5, fc6, fc7, fc6+fc7 and fine-tuned based features using ImageNet and PaHaW dataset (spiral), respectively. The Table 9 also shows the precision, sensitivity and specificity as the evaluation matrices for these experiments.

In case of reusing of fixed features case, it is concluded from series of experiments that highest accuracy 96.69% is achieved on learned features from fusion of fc6 and fc7 using ImageNet dataset. The results are less in other experiments having fixed features of fc7, fc6 and con1-conv5. as shown in table 8 and table 9. Similarly, AlexNet-freeze based features achieved 94.97%, 91.38%, 90.52% and 92.24% accuracy on MNIST using conv5, fc6 ,fc7 and fc6+fc7, respectively as shown in table 8 and table 10. The highest results up to 94.97% achieved using AlexNet-freez-MNIST at conv5 layer. While, Alexnet-finetuned based learning achieved the accuracy of 80.17% accuracy on MNIST dataset.

Fine-tune approach shows interesting results for both ImageNet and PaHaW datasets. AlexNet-finetune-ImageNet features yield outstanding result 98.28% due to large size of ImageNet dataset and 1000 classes. We assumed that MNIST dataset will perform well as compare to ImageNet dataset but AlexNet-finetune-MNIST network showed unsatisfactory per-

TABLE 7: **Results on each pattern using AlexNet-freeze-ImageNet features, AlexNet-freez-MNIST, AlexNet-finetune-ImageNet and AlexNet-finetune-MNIST on augmented PaHaW dataset**

Pattern	Samples	ImageNet conv5 fixed Features based Accuracy (%)	MNIST conv5 fixed Features based Accuracy (%)	Finetuned-ImageNet Accuracy (%)	Finetuned-MNIST Accuracy (%)
pattern-1	*spiral*	**93.10**	**94.97**	**98.28**	**80.17**
pattern-2	*Letter*	76.72	86.21	91.38	70.69
pattern-3	*twoletterword*	79.49	86.32	96.58	71.79
pattern-4	*threeletterword*	73.21	77.68	75.89	63.39
pattern-5	*shortword*	72.32	81.25	83.93	59.82
pattern-6	*twoshortword*	89.29	68.75	75.00	62.50
pattern-7	*longwords*	78.99	83.19	83.19	68.91
pattern-8	*sentence*	77.48	86.49	54.95	50.45
all patterns	all samples	87.05	74.53	84.19	77.28

TABLE 8: **Parkinson's disease identification (ImageNet-PaHaW and MNIST-PaHaW)) using different architecture of AlexNet: Reusing of Freeze layers and Fine-tune approaches of transfer learning on Pattern-1**

	Accuracy %	
Experiment	ImageNet	MNIST
conv1	49.14	50.00
conv2	45.69	74.14
conv3	54.31	93.62
conv4	62.07	92,76
conv5	93.10	**94.97**
fc6	93.97	91.38
fc7	94.83	90.52
fc6+fc7	**96.69**	92.24
Fine Tuning	**98.28**	80.17

formance and achieved 80.12% due to small size of data and 10 classes digits. Results showed that fine tuning of the ConvNet is applicable in our case due to the over-fitting concerns on MNIST daatset. From the results, we notice that in case of small and different dataset like PaHaW, it is the best choice to train a linear classifier on extracted freeze features from source datset.

TABLE 9: Performance evaluation of Parkinson's disease identification using different fixed layers in Freeze approach and Fine tuning approach of Transfer learning using ImageNet and PaHaW datasets

Experiment	Precision	Sensitivity	Specificity
conv5	91.23	82.30	91.83
fc6	94.55	89.66	94.83
fc7	95.93	90.31	95.10
fc6+fc7	97.21	91.55	98.16
Fine tuning	85.98	67.57	76.37

4.3. Validation of Dataset

Cross-validation is a statistical method that is applied for the performance evaluation of predictive model on an unknown dataset. We conducted the k-fold cross validation on single task of dataset i.e. spiral task only. The reason behind k-fold cross validation is

TABLE 10: Performance evaluation of Parkinson's disease identification using different fixed layers in Freeze approach and Fine tuning approach of Transfer learning using MNIST and PaHaW datasets

Experiment	Precision	Sensitivity	Specificity
conv5	94.74	93.10	94.83
fc6	93.55	88.66	93.83
fc7	92.73	87.93	93.10
fc6+fc7	88.89	96.55	87.93
Fine tuning	61.62	54.91	61.98

that, it guarantees that each sample eventually become the part of training as well as testing sets.The spiral sample contains 936 images. First, we divide the data into 4 folds. We have conducted the experiment in such a way that 234 images is reserved for testing and remaining 702 images in 3 folders are used for training purpose. The learning model is then trained on 3 subsets (training set) and then model is tested on the remaining subsets (test or validation set).

The overall split of the dataset for 4-fold cross validation and the results obtained by 4-fold cross validation are shown in Figure. 5. The average identification rate of 4-fold cross validation using fine-tuned features of ImageNet is computed as 98.28% ±0.38.
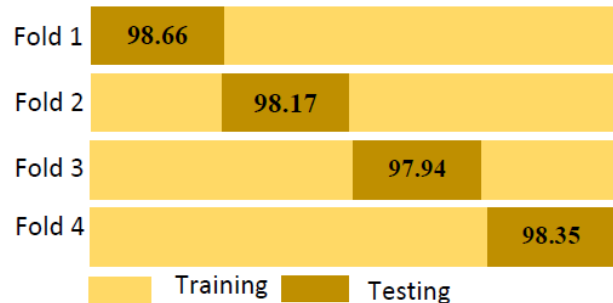

Figure 5: 4-fold cross validation

4.4. Evaluation Matrix

In order to evaluate the performance of proposed Parkinson's disease classification system, we have used sensitivity , specificity and precision as evaluation measures and performed 4-fold evaluation. Each terminology is expressed by True Positives (tp), False Positives (fp), True Negatives (tn) and False Negatives (fn) rates.

- **Accuracy** determines the overall ability of the system to correctly classify data (PD and healthy subjects)

$$Accuracy = \frac{tp + fn}{tp + tn + fp + fn}$$

- **Precision** is the true positive relevant measure and is calculated by

$$Precision = \frac{tp}{tp + fp}$$

- **Sensitivity** determine the ability of system to correctly classify the PD subjects and is defined as the proportion of True Positives in the diseased cases and calculated by

$$Sensitivity = \frac{tp}{tp + fn}$$

- **Specificity** determines the ability of the system to correctly classify the healthy subjects and is claculated by

$$Specificity = \frac{tn}{tn + fp}$$

Tables 9 and 10 depict the precision, sensitivity and specificity of various layers of Alexnet-freez-Imagenet and Alexnet-freez-MNIST. These tables aslo precision, sensitivity and specificity of the proposed systems using fine-tune approach of transfer learning using ImageNet and MNIST.

4.5. Discussion

In this section, we analyzed and compare the performance of proposed system with existing state of the art Parkinson's classification systems on PaHaW as target dataset using ImageNet and MNIST as source dataset. Table 11 describes the comparison of different Parkinson's disease classification.

A meaningful comparison of our system is possible with works of Pereira et al. [35, 36] and Moetesum et al [10]. Pereira et al. [35] applied CNN on pen based features by using three different techniques. We compare our system with his ImageNet technique outperform their work by achieving 98.19% in comparison to 80.19% using ImageNet data on time series data. In another work, they have applied meta-heuristic-based techniques that is Bat Algorithm (BA), Firey Algorithm

(FA) and Particle Swarm Optimization (PSO) in order to fine tune CNN hyper parameters [36]. Handwriting dataset has been used for detection of Parkinson's disease and provided effective results on BA approach with over all accuracy of 90.38% for spiral data. In 2018, Pereira et al. [37] combined six representations (spirals, drawing of circles on the page and in air, meanders, left-wrist and right-wrist movements) and extracted features by deploying CNN using pen based features (time series) from online images and reported about 93.50% accuracy. In both studies, time series data was used. In comparison to Pereira et al. [35–37], our system showed consider gain in performance i.e. 80.19% [35], 90.38% [36], and 93.50 [37] to 98.28%.

Moetesum applied pre-trained AlexNet-freeze-ImagNet for feature extraction using three representations of offline images in input space and then apply SVM for classification using visual attributes yielded 83% [10]. However, in this work, we have applied the same model but further explore the performance of CNN model named as AlexNet architecture for different patterns of PaHaW dataset and investigated thoroughly the three common approaches i.e., scratch, freeze or fixed features and fine-tune features. Results of [10] showed that basic approach showed poor performance. To improve the classification performance, we have used two different source datasets (ImageNet and MNIST) and their impact on PD identification. To increase the size of training dataset, we have used different techniques of data augmentation (rotation, fliping, contour etc) with raw images. In reusing of freeze features of transfer learning, we thoroughly explored features at each layer and fusion of fc6 and fc7. The conv5 layer based features showed highest identification rate in case of AlexNet-freez-MNIST up to 94.97% (96.34% precision) and then pass the learned features to a linear SVM model for classification and identification of PD and H instance. The finetune-MNIST features based networks showed less accuracy as compare to other networks. In proposed study, ImageNet finetuned based approach outperformed and achieved 98.28% accuracy as compare to the accuracy (96.69% accuracy (97.21% precision) based on the fusion of fc6 and fc7 using AlexNet-freeze-ImageNet features on spiral drawing patterns.

Our proposed system showed the promising results on PaHaW (spiral data) using different approaches of deep transfer learning and of data-augmentation based techniques as compare to the existing studies in the literature.

5. Conclusion

Parkinson's Disease (PD) is hot neurological problem nowadays and the diagnosis of PD at early stages can cure PD and saves patient's life. In this study, we cope with the problem of Parkinson's disease identification through deep learner. For this purpose, we

TABLE 11: **Performance comparison of Parkinson's disease detection system**

Study	Features	Classifier	Dataset	Accuracy (%)
Pereira et al. [35]	Pen base features	CNN	HandPD	80.19
Pereira et al. [36]	Pen base features	CNN	HandPD	90.38
Pereira et al. [37]	CNN based features	CNN	HandPD	93.50
Moetesum et al. [40]	AlexNet-freeze-ImageNet features from fc7 layer	SVM	PaHaW	83
Proposed System	AlexNet-freeze-MNIST features fron conv5 layer	SVM	PaHaW	94.97
Proposed System	AlexNet-freeze-ImageNet features from fc6+fc7 layers	SVM	PaHaW	96.69
Proposed System	Fine-tuned-ImageNet features	AlexNet	PaHaW	98.28

considered the non-invasive method using handwriting images for detection of PD. The AlexNet classifier with transfer learning technique is proposed for detection of handwriting impairments in Parkinson's patients so as improving the diagnosis of PD. Basically, the idea is to model the handwriting features from AlexNet and transfer these features to our target data due to finite number of samples. So for, we have used the pre-trained Alexnet-ImageNet and AlexNet-MNIST. We explored the two common approaches (Freeze and fine-tuning) for transfer learning using two different source datasets (MNIST and ImageNet). The Fine-tuned approach of transfer learning using ImageNet proved to be an efficient feature extraction approach and outperformed the state of the art systems . Without extraction of traditional features, CNN system achieved accuracy of 98.28% on spiral pattern. The advantages of the proposed deep learner classifier summarized as follows. The proposed classifier has the capacity to automatically extract hidden features, which extensively increases the performance of the classifier. Parkinsons disease can be diagnosed remotely and monitored using the proposed classifier. Therefore, patients rarely need to make visits to the clinic. The deep learner classifier can be used as a reliable classifier for the PD, results show that the proposed classifier outperforms the conventional methods. From proposed study, we concluded that spiral images for Parkinson's detection is more informative as compared to letters, words and sentences. As PaHaW dataset contains less spiral pattern that we increases by data augmentation but collection of huge amount of spiral dataset consider more efficient for Parkinson's detection.

In regard to future work, we aim to extend our study to other deep learner models (Google-net, resnet and VGG) and compare their performance on PaHaW dataset, HandPD dataset or combination drawing of both. We also extend our work to other dataset of Parkinson's disease i.e. voice and images dataset for effective diagnosis of Parkinson's.

6. Conflict of Interest

The authors whose names are listed in this paper certify that they have NO conflict of interest.

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