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Early detection of neurodegenerative diseases by handwriting analysis

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Abstract

Neurodegenerative diseases are among the most common diseases of our time, Parkinson is our primary goal in this thesis by identifying it in handwriting using deep learning and convolutional neural networks (CNN), where we used transfer learning (vgg16 vgg19) in addition to two other types of convolutional neural networks (CNN3, CNN4)

With a data set (handPD, NewhandPD, drawing) for Parkinson's disease by handwriting. The outcomes demonstrated that for (VGG16 and VGG19, our accuracy was excellent and very reasonable, reaching 100% in Drawing dataset. The accuracy of the CNN4 and CNN3 models was 90, 74% in handPD dataset and 96, 29 % in NewhandPD, respectively. the results showed that we can analyze the handwriting of Parkinson's disease using these models.

keywords: Neurodegenerative diseases, Parkinson’s diseas, deep learning, convolutional neural networks, handPD, NewhandPD , parkinson drawing , handwriting.

Résumé

Les maladies neurales sont parmi les maladies les plus courantes de notre époque, et le Parkinson est notre objectif principal dans cette thèse en l'identifiant à l'écriture manuscrite à l'aide d'apprentissage en profondeur et de réseaux de neurones convolutifs (CNN), où nous avons utilisé l'apprentissage par transfert (vgg16 vgg19) en plus à deux autres types de réseaux de neurones convolutifs (CNN3, CNN4)

Avec un jeu de données (handPD, Drawing, NewhandPD) pour la maladie de Parkinson par écriture manuscrite. Les résultats ont démontré que pour (VGG16 et VGG19, notre précision était excellente et très raisonnable, atteignant 100 % dans l'ensemble de données de dessin. La précision des modèles CNN4 et CNN3 était de 90,74% dans l'ensemble de données handPD et de 96,29% dans NewhandPD, respectivement. Les résultats ont montré que nous pouvons analyser l'écriture manuscrite de la maladie de Parkinson à l'aide de ces modèles.

Mots-clés : Les maladies neurales, maladie de parkinson, apprentissage profond, réseaux de neurones convolutifs, handPD, NewhandPD, drawing de parkinson, écriture manuscrite.

الملخص

تعد الأمراض العصبية من أكثر الأمراض شيوعًا في عصرنا، ومرض باركنسون هو هدفنا الأساسي في هذه الأطروحة من خلال تحديده في الكتابة اليدوية باستخدام التعلم العميق والشبكات العصبية التلافيفية (CNN)، حيث استخدمنا التعلم التحويلي (vgg16, vgg19) بالإضافة إلى ذلك. إلى نوعين آخرين من الشبكات العصبية التلافيفية (CNN3، CNN4)

مع مجموعة بيانات (handPD , NewhandPD ,drawing) لمرض باركنسون عن طريق الكتابة اليدوية. أظهرت النتائج أنه بالنسبة لـ (VGG16 وVGG19)، كانت دقتنا ممتازة ومعقولة جدًا، ووصلت إلى 100٪ في مجموعة بيانات الرسم. بلغت دقة نماذج CNN4 وCNN3 في مجموعة بيانات 90.74 ٪ في مجموعة بيانات handPD و٪ 96.29 في NewhandPD، على التوالي. وأظهرت النتائج أنه يمكننا تحليل خط اليد لمرض باركنسون باستخدام هذه النماذج.

الكلمات المفتاحية: الأمراض العصبية، مرض باركنسون، التعلم العميق، الشبكات العصبية التلافيفية، handPD، NewhandPD، Drawing ، الكتابة اليدوية

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List of Abbreviations

NDs	*neurodegenerative diseases*
AD	Alzheimer's and Parkinson's
PD	Parkinson disease
AI	Artificial Intelligence
ML	Machine learning
DL	Deep Learning
ANN	Artificial Neural Networks
RNNs	Recurrent Neural Networks
CNN	Convolutional Neural Network
FC layers	fully connected layers
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

ACC	Accuracy
SEN	Sensitivity
SPE	specificity
SP	Spiral
ME	Meander
CI	Circle
WA	Wave

General Introduction

Neurodegenerative diseases are characterized by the loss of nerve cells in the brain and spinal cord **[1].** And this leads to changes in the function of the nervous system, affecting the control of senses, movement, and mental functions. Among these neurological diseases, we find Alzheimer’s disease and PD

as Alzheimer’s disease (AD) leads to a widespread loss of neurons, while Parkinson’s disease (PD) results in a specific loss of dopaminergic neurons in the substantia nigra **[1].** in addition to being considered a chronic motor neuron disorder due to the fact that it is characterized by a group of motor symptoms. Such as tremor, weakness, and an inability to move. Parkinson's disease (PD) may also be accompanied by other symptoms such as depression, anxiety, fatigue, and difficulty sleeping.

Deep learning has had a significant impact on many areas of artificial intelligence, and among these areas is the recognition of Parkinson's disease by using handwriting, as there are two types of handwriting recognition systems: offline recognition and online recognition.

The main focus of our presented thesis is to create models with convolutional neural networks to manually classify Parkinson's disease cases (patient and non-patient) using a dataset in the form of images, which are three (drawing, HandPD, and NewHanPD), and our first step was to use pre-trained models (transfer learning of two types, vgg16 and vgg19) to see if the results are good or not on Parkinson's disease, then we introduce two more models (CNN3 and CNN4), which are models that minimize the number of layers of the convolutional neural network. The aim is to see if reducing the number of strata gives good results in classifying Parkinson's disease without adding any auxiliary models to improve it.

We have divided our work into two main parts:

Part One, "State of the Art," is divided into two chapters.

- **Chapter 01:" *Basic concepts"***

In this chapter, we have talked about the two types of neurological diseases, especially Parkinson's disease. We also studied deep learning in general, especially convolutional neural networks and everything they involve, as well as handwriting reconnection.

- **Chapter 02:" Detection of Parkinson's with handwriting Analysing"**

In this chapter, we talked about how to analyze and influence Parkinson's disease on handwriting, and we also examined some of the work that has been done regarding Parkinson's disease and handwriting from 2013–2022.

Part Two: "Practical Study" is divided into two chapters.

- **Chapter 03:" Experimental implementation and results"**

We talked about the methods and tools used and everything related to the action steps that were applied to the proposed model, which is the transfer of learning of both types (vgg16 and vgg19). Finally, we interpreted and compared the results that we obtained.

- **Chapter 04:" suggestion of two deep learning models (CNN3, CNN4) for detection of Parkinson's disease"**

In this chapter, we propose two new models (CNN3 and CNN4) without the need to add other auxiliary models. We also applied several steps to train and test the two models, we analysed the four models (vgg16, vgg19, cnn3, and cnn4) and compared them with previous works.

PART ONE

STATE OF THE ART

CHAPTER 01

BASIC CONCEPTS

I. Introduction

In this chapter, we present a summary of the ideas and methods that we dealt with during this work. It is known that in recent times technology and artificial intelligence have witnessed a great development and use in various areas of life, including health care, where neurological diseases are among the most common diseases, as they affect the nervous system. It causes a group of symptoms and psychological and physical disorders. Among these neurological diseases, we find Parkinson’s disease. In this work, we referred to the stages of its development, knowledge of its various symptoms, the reasons that led to its appearance and how it is diagnosed and treated, in addition to that we talked about deep learning and neural networks Bypass Then we touched on how the computer recognizes handwriting

II. Part one: neurodegenerative diseases

1. Neurodegenerative diseases

The two prevalent neurodegenerative diseases, Alzheimer's and Parkinson's, afflict millions of individuals globally, and it is predicted that over the next few decades, their incidence will significantly rise. Although these diseases cannot be cured, early detection can help to better control their symptoms and course of development. These factors clarify why it is crucial to provide support networks for the early diagnosis of (NDs). One of the skills that is impacted by NDs is handwriting. Because of this, researchers have also looked into the idea of using handwriting changes brought on by NDs as diagnostic indicators. This study reviews the research on using handwriting analysis to help the diagnosis of moderate cognitive impairment (MCI), Alzheimer's disease, and Parkinson's disease **[2].**

1.1. Types of neurodegenerative diseases

1.1.1. Alzheimer’s disease

The increased life expectancy of the general population and a greater understanding of the socioeconomic effects of the disease have made Alzheimer's disease (AD) a serious public health issue. Alois Alzheimer used pathological indicators, such as increasing memory loss and disorientation, and other criteria to identify it in 1906.

At first, AD was thought to be an uncommon disorder, and subsequently, it was believed to be a natural part of getting older. Ageing stigma and other reasons hinder intensive research into and treatment of AD patients, but these misunderstandings are dissipating, and therapies, if initially of moderate efficacy, are starting to become accessible **[3].**

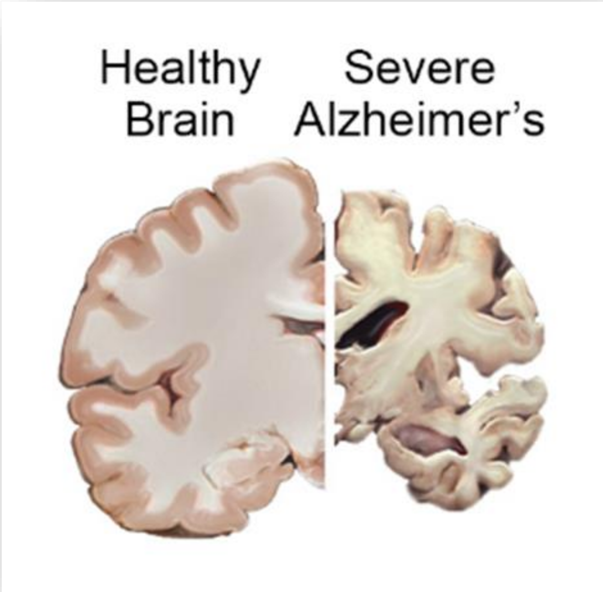


Figure 1. 1 : Alzheimer Disease [4]

1.1.2. Parkinson's disease

Movement, speech, and posture may all be impacted by Parkinson disease, a degenerative condition of the central nervous system. Muscle rigidity, tremor, slowing of physical motion, and in severe cases, loss of physical motion are frequently present. The main signs and symptoms are brought on by abnormal muscle contractions, which are brought on by a lack of dopamine production in the brain's dopaminergic neurons (substantia nigra), which are responsible for producing the chemical **[5]**.

Although almost anyone is at risk of developing Parkinson's, some studies indicate that men are more likely than women to be affected by this condition. It's unclear why, but research is being done to identify potential risk factors.

Age is an obvious risk. Although about 5% to 10% of Parkinson's patients experience onset before the age of 50, the disease typically first manifests in those over the age of 60. Parkinson's disease with an early onset is frequently inherited; however, this is not always the case, and some kinds have been connected to particular genetic alterations. **[6]**

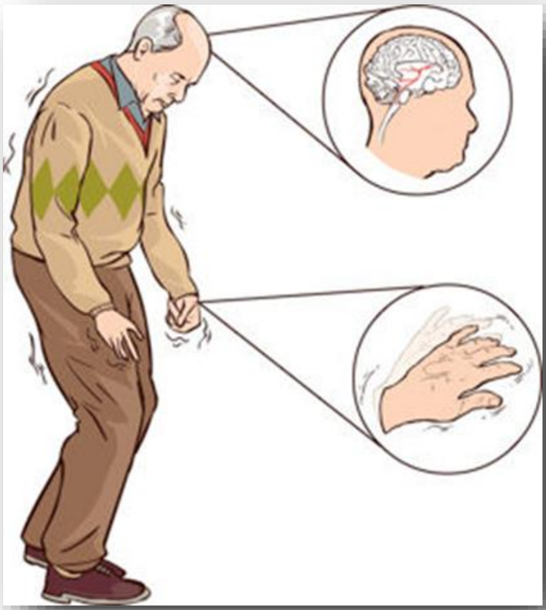


Figure 1. 2 : Parkinson's Disease [7]

1.1.2.1. The stages of Parkinson's disease

Each disease has distinct stages in which it manifests, and Parkinson's disease goes through five of these stages: **[8]**

- **Stages 01**

In the beginning, the person only experiences minor symptoms that, in most cases, do not hinder daily activities. Tremors and other indications of movement are only present on one side of the body. There are modifications to walking, facial expressions, and posture.

- **Stages 02**

The symptoms start to deteriorate. The midline (such as the neck and trunk) or both sides of the body are affected by tremor, stiffness, and other movement abnormalities. It's possible to see issues with posture and walking. Although the individual may live alone, everyday chores are more challenging and time-consuming.

- **Stage 03**

Disabilities are mild to moderate in this stage, with loss of balance (such as unsteadiness when a person turns or when a person is pushed from a standing position) being the hallmark, occasional falls occurring, and motor symptoms worsening. Functionally, a person carries out their daily activities in a limited way but is still physically able to lead an independent life.

- **Stage 04**

The symptoms are now fully developed and quite incapacitating. The person can still stand and walk unaided, but for safety, they may need to use a cane or walker. The person is unable to live alone and requires extensive assistance with daily activities.

- **Stage 05**

The most severe and advanced stage is this one. Standing or walking may be impossible due to leg stiffness. Unless assisted, the person is bedridden or restricted to a wheelchair. All activities demand round-the-clock care.

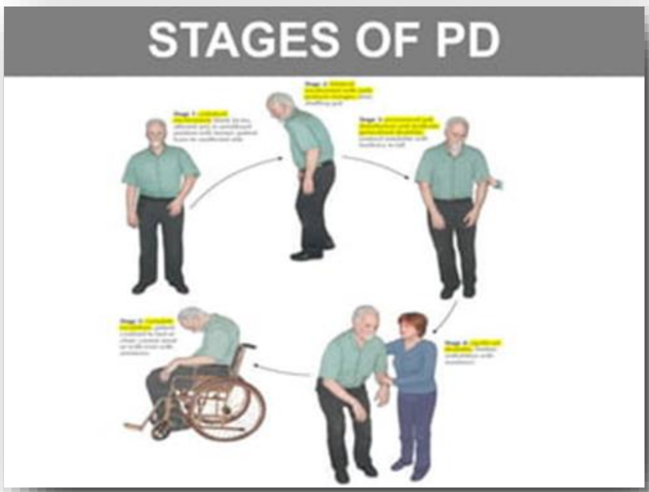


Figure 1. 3: Stage of Parkinson's Disease [9]

1.1.2.2. causes of Parkinson’s disease

Parkinson's is a central nervous system disorder brought on by the death of dopamine-producing brain cells. It is unknown why dopamine-producing cells go, though. According to research, a confluence of genetic and environmental variables may be to blame. Depending on the individual, these two elements may or may not interact **[10].**

1.1.2.3. symptoms of Parkinson’s disease

There are four key signs of Parkinson's disease: **[6]**

- Hand, arm, leg, jaw, or head tremor
- Muscle stiffness, where a muscle remains contracted for a prolonged period of time
- Movement is slowly
- Impaired coordination and balance, which can occasionally result in falls

Figure 1. 4: Symptoms of Parkinson 's Disease [11]

1.1.2.4. Diagnosis of Parkinson’s disease

The diagnosis of idiopathic Parkinson's disease is still made clinically, despite advancements in radiologic testing. The following cardinal signs must be present in order to make a diagnosis: rigidity, bradykinesia, and a 3 to 6 Hz distal resting tremor **[12]**

Doctors typically conduct a neurological exam and obtain a patient's medical history to determine the disease. A If someone's symptoms improve once they begin taking medication, there is another indication that they have Parkinson's disease.

Many conditions can produce symptoms resembling those of Parkinson's disease. is the term for people who exhibit Parkinson's-like symptoms due to other conditions like atrophy of several systems and Lewy body dementia. The results of specific medical tests and the effects of drug therapy may help identify the true cause of these conditions, even though they may initially be mistakenly diagnosed as Parkinson's. Since many other illnesses share symptoms with the one you have but need different treatments, it's crucial to get a proper diagnosis **[6].**

1.1.2.5. Treatments for Parkinson’s disease

Over the past 50 years, there have been significant advancements. Despite advances in Parkinson's disease (PD) treatment, levodopa is still the best medication for managing PD symptoms. An accurate diagnosis of PD must be made before beginning medical treatment, and the degree It is necessary to evaluate each type of dysfunction (motor, sensory, autonomic, and mental). There are also other medications available in addition to levodopa, and each patient's therapy must be tailored. The differences between catechol-o-methyl-transferase, dopamine agonists (DA), and these substances are related to how they affect dyskinesias and motor fluctuations. **[13]**

III. Part two: deep learning

1. deep learning

1.1. Artificial Intelligence (AI)

Artificial intelligence is essentially a means for transferring human intelligence to machines through a system of rules (an algorithm). The term artificial intelligence is made up of the terms "artificial" and "intelligence," where "artificial" refers to human-made or non-natural objects and "intelligence" refers to the capacity for understanding or rational thought **[14]**. Compared to visual pattern recognition, complicated decision-making, and the use of natural language, early AI initiatives, like playing chess and solving mathematical problems, are now viewed as trivial. as well as the Turing test **[15].**

1.2. Machine learning (ML)

In order to execute classification and prediction tasks on new data, machine learning seeks to build computer systems that identify patterns in training data. Models are created using a combination of methods from machine learning, data mining, and optimization **[16].**

1.3. Deep Learning (DL)

Deep learning is essentially a subset of the wider field of machine learning that employs neural networks to replicate the operation of the human brain. Neural networks are analogous to the neurons in our brain. In order to possibly find patterns and classify the information in accordance with those patterns, DL algorithms concentrate on mechanisms for information processing patterns **[14].**

1.4. Difference between Artificial Intelligence VS Machine Learning VS Deep Learning

Basis for comparison	Artificial Intelligence	Machine Learning	Deep Learning
Subset	AI does not fall under the categories of machine learning or deep learning.	Artificial intelligence includes machine learning as a subset.	Machine learning includes deep learning as a subset.
Programming	To construct an AI system, complete programming is necessary.	No programmed algorithms are required for machine learning.	Programming is not necessary for deep learning to work.
Complexity	AI is more complicated since it requires total knowledge.	Compared to AI, machine learning is less difficult.	Machine learning is more complicated than deep learning.
Existence	1956	1980's	2000
Examples	Amazon Echon	Search engine result refining	Automatic translation

Table 1. 1: DIFFERENCE BETWEEN AI VS ML VS DL [17]

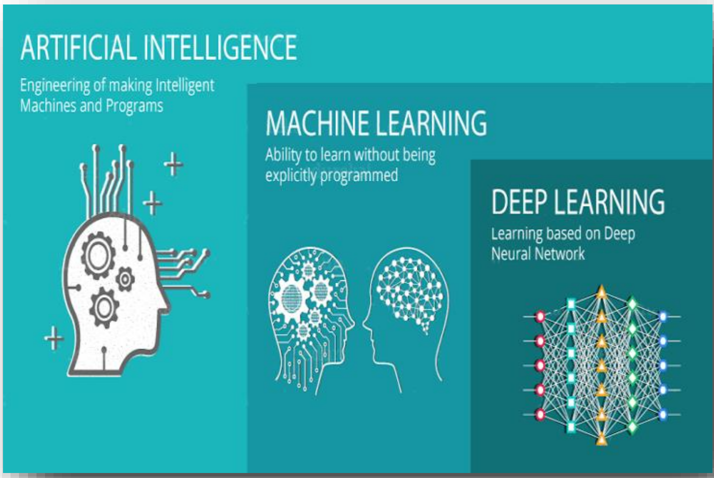


Figure 1. 5 :AI VS ML VS DL [18]

2. Types of Neural Networks in Deep Learning

2.1. Artificial Neural Networks (ANN)

An artificial neural network is a device that is somewhat based on the human brain. Numerous terms are used to describe the area, including connectionism; parallel distributed processing, neuro computing, natural intelligence systems, machine learning techniques, and artificial neural networks. It is an effort to replicate many layers of basic processing units, called neurons, using specialised hardware or complex software. With various coefficients of connectivity that describe the intensity of these connections, each neuron is connected to some of its neighbours. By changing these strengths, the network as a whole can provide outcomes that are suitable **[19].**

2.2. Recurrent Neural Networks (RNNs)

The neural network architecture known as recurrent neural networks is another specialised design. RNNs are designed to address learning issues where previous data (i.e., past instants/events) is directly related to making predictions about the future. Such sequential examples are commonly utilised in various real-world applications, such as language modelling, where the words that came before the next one in the sentence are used to predict what word will come next.

The most recent stock prices, whether they be hourly, daily, or weekly, also serve as a predictor of future stock movement. RNNs are especially suited to applications involving time series or sequential data **[20].**

2.3. Convolutional Neural Network (CNN)

Neural networks with convolutions are a subset of deep learning techniques that have gained prominence in a number of computer vision applications and are gaining traction in a number of fields, including radiology. Convolutional neural networks use a backpropagation technique to adapt and automatically learn spatial hierarchies of feature sets. CNN is constructed using a number of building blocks, such as**: [21]**

- ❖ convolution layers
- ❖ Non-linear activation functions (ReLU)
- ❖ pooling layers
- ❖ fully connected layers

2.3.1.Convolutional Neural Network Layers

The CNN architecture consists of a series of layers (or the so -called multiple construction blocks). Each CNN architecture layer, including its function, is described in detail below **[22].**

2.3.1.1. Convolutional Layer

In the CNN architecture, the wealth layer is the most important element. It consists of a set of weave filters (so -called kernels)). The input image, expressed as N-dimensional indicators, is coupled with these filters to generate the map of the output function: **[22]**

- **Kernel definition**

The kernel can be visualised as a grid of discrete integers or values. The kernel weight is referred to for each value. When CNN training first starts, random numbers are chosen to serve as the kernel weights. Additionally, there are various techniques for initialising the weights. Then, these weights are changed during each training period, teaching the kernel to extract important proper-ties **[22].**

- **Convolutional Operation:**

Initially, the CNN input format is explained. The multichannel image is the input of the CNN, whereas the vector format is the input of the conventional neural network. Gray-scale images, for example, are single-channel, whereas RGB images are three-channeled. To better understand the convolutional operation, consider a 4x4 gray-scale image with a 2x2 random weight-initialized kernel. First, the kernel moves horizontally and vertically across the entire image. Furthermore, Calculating the dot product between the kernel and the input image involves multiplying and summing the corresponding values to simultaneously calculate multiple factors and produce a single scalar value. After then, up until there is no more sliding possible, the process is repeated. It should be noted that the feature map of the output is represented by the computed dot product values. graphically depicts the primary computations performed at each stage. The light green hue in this picture indicates the 2x2 kernel, whereas the light blue color shows the equivalent size region of the input image. Both are multiplied, the total of the resultant product values (shown in light orange) indicates the feature map of the output is represented by the computed dot product values **[22].**

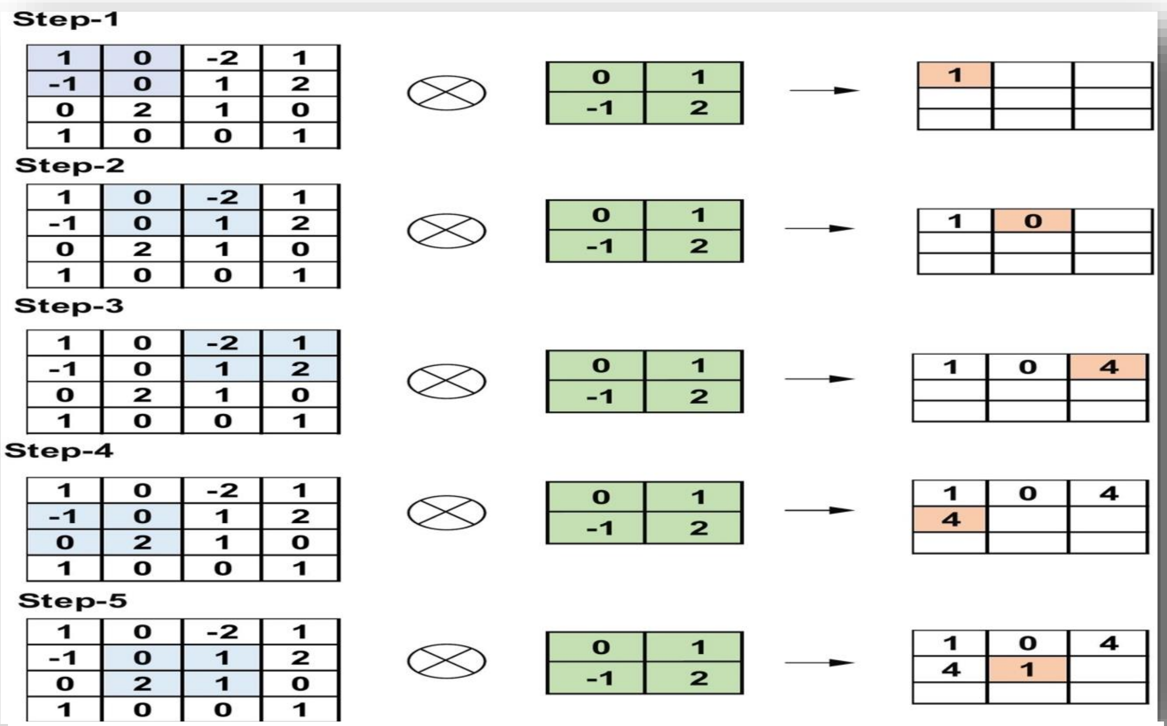


Figure 1. 6:The primary calculations executed at each step of convolutional layer [22]

However, in the preceding example, no padding is added to the input picture, but a stride of one is applied to the kernel (denoted for the chosen step-size across all horizontal or vertical positions, it should be noted that another stride value is also an option. In addition, increasing the stride value yields a feature map with lower dimensions. Padding, on the other hand, is crucial in determining border size information for the input image. The border side-features, on the other hand, move very quickly. Padding increases the size of the input image, which in turn increases the size of the output feature map. The Primary Advantages of Convolutional Layers **[22].**

- **Sparse Connectivity**

In FC neural networks, every neuron in one layer communicates with every neuron in the layer above it. In contrast, there aren't many weights available between two adjacent layers in CNNs. As a result, there aren't many weights or connections needed, and storing those weights doesn't take up much memory, making this approach memory-efficient. In CNN, the matrix operation is also much more computationally expensive than the dot (.) operation **[22].**

- **Weight Sharing**

In CNN, there are no weights assigned to any pairs of neurons in adjacent layers because each weight operates on a single input matrix pixel. Due to the lack of additional weights for each neuron, training time and expense are considerably decreased by learning just one set of weights for the entire input **[22].**

2.3.1.2. Activation Function (non-linearity)

All layers containing weights (also referred to as learnable layers, such as convolutional and FC layers) in the CNN architecture are followed by non-linear activation layers. The activation layers' nonlinear behaviour indicates that the input-to-output mapping will also be nonlinear. Additionally, CNN can learn incredibly sophisticated things thanks to these layers. In order to train the network via error back-propagation, the activation function also needs to be able to distinguish between distinct inputs, which is a crucial aspect. Most Following are some examples of activation function categories used by deep neural networks and CNNs **[22]:**

- ✓ **ReLU**: The CNN context's most often used function It changes the input's entire values to positive numbers. ReLU has an advantage over the others in that it requires less calculation. contains a mathematical representation of it **Figure 1.7: [22].**

$$f(x)_{ReLU} = max(0, x)$$

Figure 1. 7:function of ReLU [22]

- ✓ **Tanh:** It resembles the sigmoid function in that real values are used as input, but the result may only be between 0 and 1, giving it a mathematical representation **Figure 1.**8 **[22].**

$$f(x)_{tanh} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Figure 1. 8 : function of tanh[22]

- ✓ **Sigmoid:** This activation function only accepts real values as input, and its output ranges from zero to one. The mathematical representation of the sigmoid function curve, which has an S shape, **Figure 1.9 [22].**

$$f(x)_{sigm} = \frac{1}{1 + e^{-x}}$$

Figure 1. 9 : function of Sigmoid [22]

2.3.1.3. Pooling Layer

The main task of the merger layer is to subsample the functional card. These cards are generated by folding operations. In other words, this method reduces large functional cards to create smaller functional cards. At the same time, it maintains most of the leading information (or features) in each step of the merger process. Similar to folding, before the merger operation, the steps and the coreor are the first size observations.

Various types of mergers can be used for various pools. These methods include tree mergers, closed-type mergers, average bundles, mines, the world's largest pools, global average pools (GAP), and the world's largest officials. The most famous and commonly used mergers are the maximum, minimum, and gap mergers. Figure 1.10 shows these three combined operations [20]. The grouping operation summarises the characteristics present in a region, whose size the grouping filter determines. If a filter has 2x2 dimensions, then the region that is summarised also has 2x2 dimensions. Recall that a filter's size is typically smaller compared to a feature map **[23].**

- **Types of pooling layers**

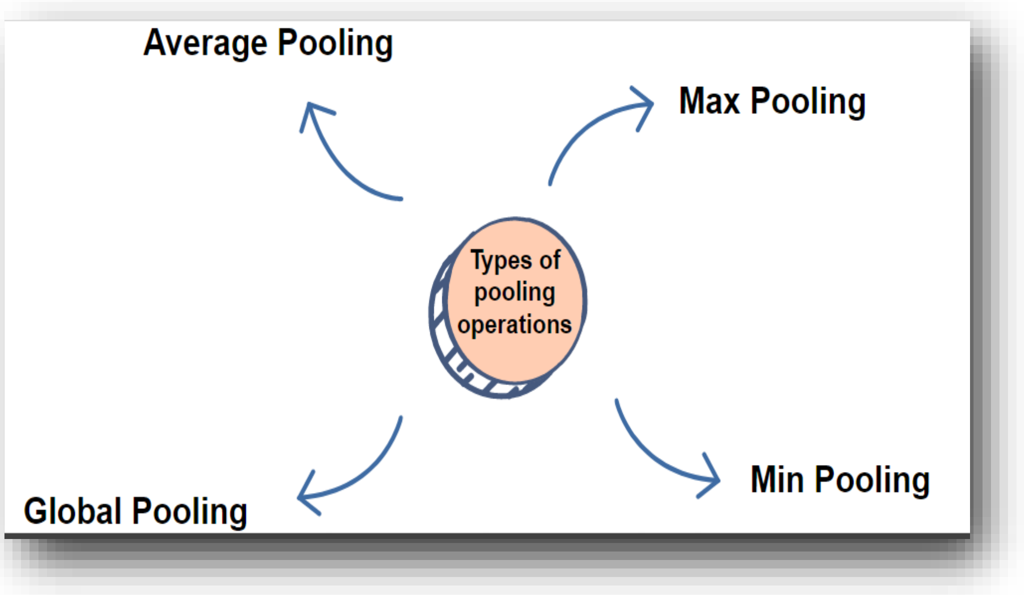


Figure 1. 10: Types of pooling layers [23]

✓ Max Pooling

In this kind of pooling, the largest value inside an area serves as a representation of the features in that region as a whole. Since max pooling will choose brighter pixels when an image has a dark background, it is typically employed in those situations **[23].**

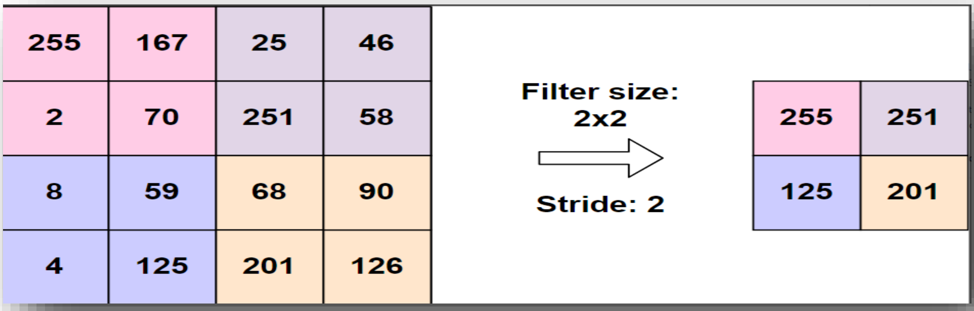


Figure 1. 11 :MAX POOLING [23]

✓ Min Pooling

In this type of grouping, the summary of the characteristics in a region is represented by the minimum value in that region. It is mainly used when the image has a light background since the minimum group will select darker pixels **[23].**

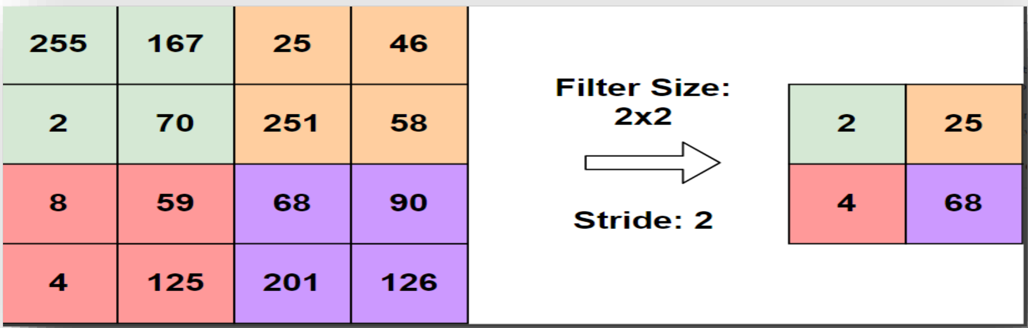


Figure 1. 12 : Min POOLING [23]

✓ Average Pooling

In the third type of pooling, the average value for a region serves as a representation of the features in that region as a whole. When these edges are not crucial, average pooling is used to soften the sharp edges of a picture **[23].**

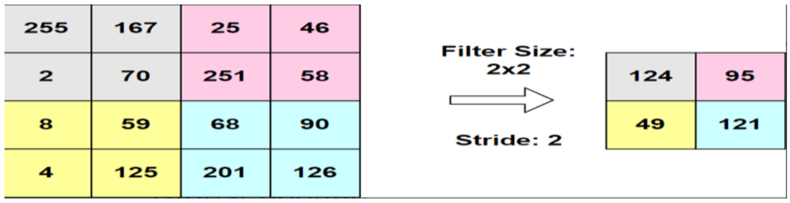


Figure 1. 13: AVERAGE POOLING [23]

✓ Global pooling

Reduces each channel in the feature map to only one value. The value is determined by the type of global aggregation; it can be any of the types listed previously. Global aggregation is analogous to applying a filter to a feature map's exact dimensions **[23].**

2.3.1.4. Fully Connected Layer

The output of the last pooling layer of a convolutional neural network serves as the input for the fully connected layer at its conclusion. There may be one or more of these layers. All first-layer nodes are connected to all second-layer nodes when a system is fully connected **[24].**

2.3.2. The architectures in CNN

There are many existing architectures in CNN; some of the most popular ones are LeNet-5, AlexNet, and VGGNet **[25].**

2.3.2.1. LeNet-5

Yann LeCun and his co-workers at Bell Labs suggested the LeNet-5 as the first CNN in 1998. This network was created specifically for digit recognition. The method was successfully commercially deployed for handwritten signature detection in checks. Because of technological constraints at the time, it is only made up of a few layers and filters. The architecture comprises:**[25]**

- two convolution layers
- two average pooling layers
- two fully connected layers
- an output layer with a Gaussian connection
- LeNet-5 has 60,000 parameters. Tanh activation function is used.

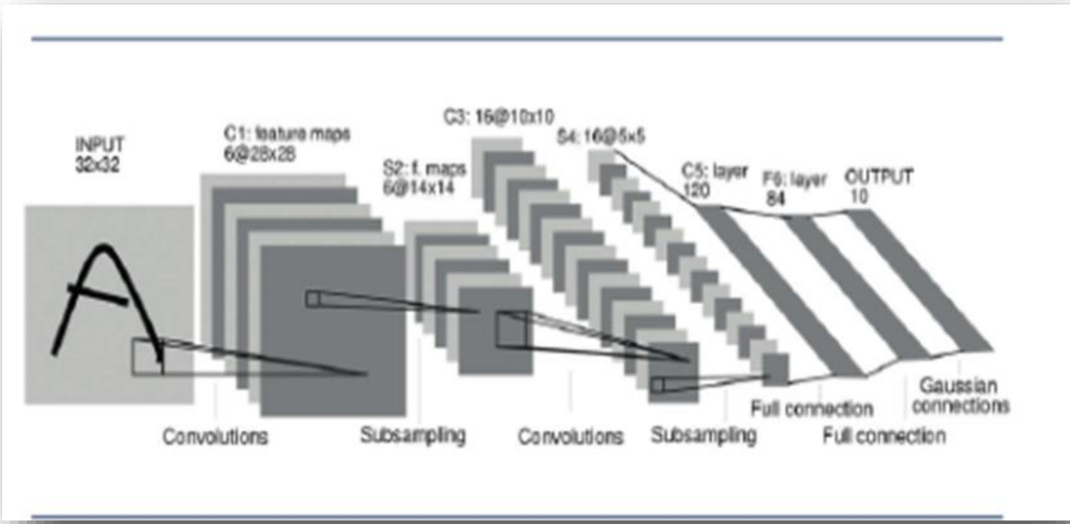


Figure 1. 14:ARCHITECTURES FOR LENET- 5[25]

2.3.2.2. AlexNet

The AlexNet architecture, which won the 2012 Image Net ILSVRC competition, was the first work to popularise convolutional networks in computer vision. Its top-five error rate was 15.4%, compared to 26.2% for the next-lowest network.

AlexNet's architecture is similar to that of LeNet-5, but it is deeper, larger, and made up of convolutional layers that are stacked on top of one another. The Tanh activation function that was used in LeNet-5 has been replaced with the ReLU function, and as a loss function, the cross-entropy loss function is used. was trained using the MNIST dataset, which had 50,000 pictures and 10 categories, whereas AlexNet utilised a subset of the ImageNet dataset with a training set made up of one million colour images and 1000 categories **[25].**

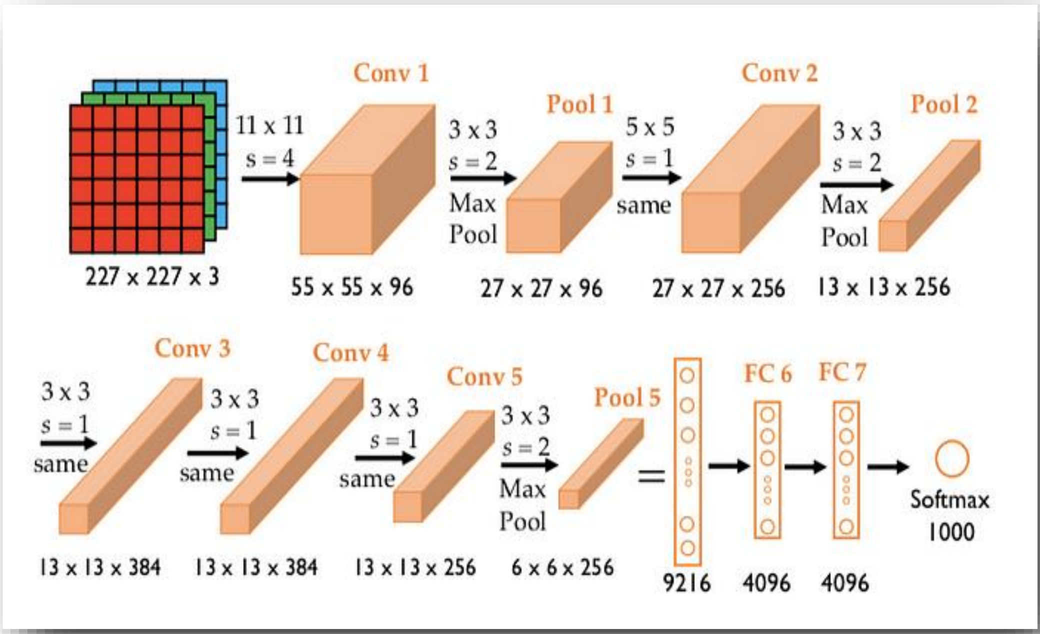


Figure 1. 15:AlexNet Architecture[26]

2.3.2.3. VGGNet

The VGG Network is introduced in 2014 by Andrew Zisserman and Karen Simonyan. It was viewed as a very deep network at the time. Its main contribution was to demonstrate how important network depth is to improving CNNs' ability to recognize or classify objects accurately. The authors explain that the 3x3 filters used by the VGGNet in fig 1.9. give a field of reception of 7 by 7 filters when used in three sets and an effective responsive the field of 5 by 5 filters when used in two consecutive sets. The filter count of the architecture doubles with each max-pooling operation. **[25]**

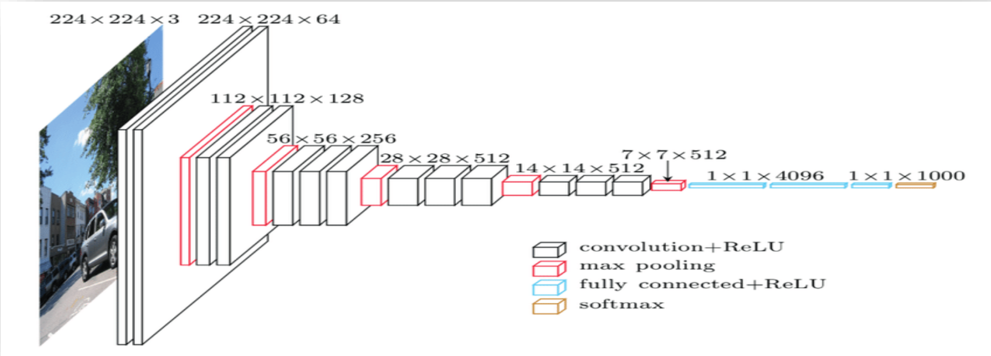


Figure 1. 16:ARCHITECTURE VGGNET [25]

IV. Part three: handwriting recognition

1. handwriting recognition

A computer's capacity to recognise and understand legible handwriting on paper documents, touch screens, photos, and other media is known as handwriting detection. Online and offline recognition of handwriting are two traditional divisions. While only the image of the text is available for offline recognition, online recognition records a time series of coordinates representing the movement of the pen tip **[27].** OCR is the most widely used method for handwriting recognition. We can scan handwritten manuscripts and use computer vision to translate them into simple text **[28].**

1.1. Types of handwriting recognition

1.1.1.On-line

Online recognition is the process by which a computer reads each character as it is written. A pen-equipped electronic tablet is the preferred type of input device. With a resolution of 10 points per inch, a sampling rate of 100 points per inch, and an indication of pen-up and pen-down, the electronic tablet records the x-y coordinate data of pen-tip movement. In other words, a series of coordinate points with distinct stroke indications are used to record the outline of the handwriting or line drawing **[29].**

1.1.2.Off-line

Following the completion of the writing, offline handwriting recognition is carried out. It may be carried out days, months, or even years later. The writing's picture is transformed into a bit pattern via an optical scanner. Scanners typically have x and y resolutions of 300–400 points/in. OCR's offline handwriting recognition is a subset of that technology. There has been a lot of work done on handwriting as well, despite the fact that machine-printed characters have received the majority of OCR work. Hundreds of characters are frequently processed by OCR systems every second **[30].**

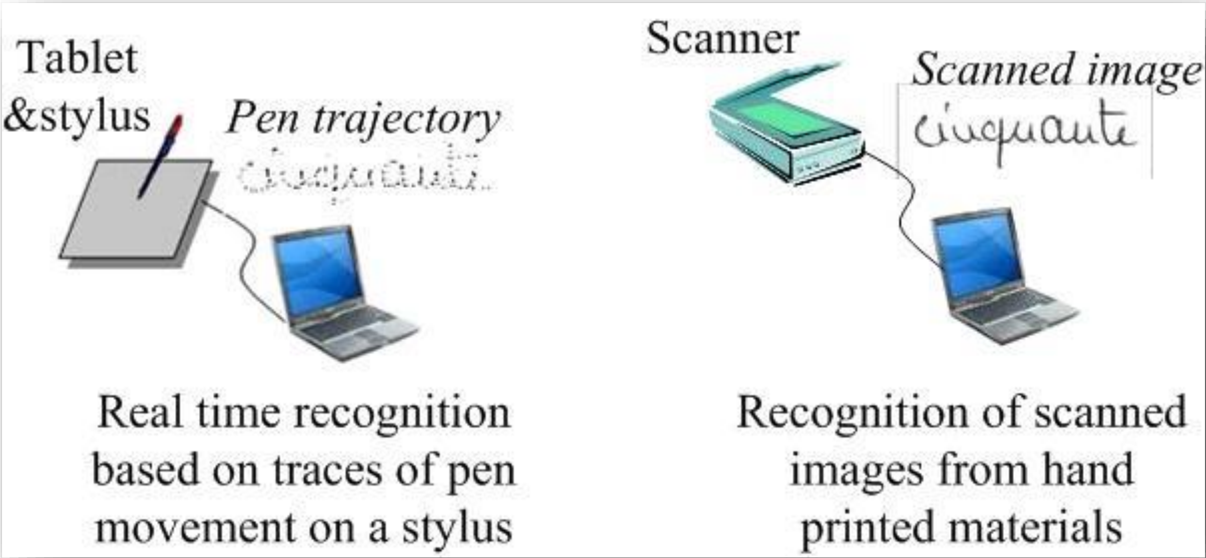


Figure 1. 17:Online vs. Offline handwriting system [28]

V. Conclusion

We conclude from the foregoing that despite the ongoing research on Parkinson's disease, no specific treatment or preventive measure has been reached so far. It is possible to live with this disease by changing the lifestyle in order to alleviate the symptoms, and since Parkinson's disease affects movement (writing). In the second axis, we tried to study the relationship between Parkinson's and handwriting

CHAPTER 02

DETECTION OF PARKINSON'S WITH HANDWRITING ANALYSING

1. Introduction

In this chapter, we have attempted to provide a set of ideas regarding the relationship of handwriting to Parkinson's disease. Recently, there has been significant research interest in creating automated systems for the purpose of detecting the early stages of Parkinson's disease based on handwriting data. Through this work, we touched on the knowledge of handwriting analysis in Parkinson's disease and how this disease affects handwriting through our study of many works to know the data sets they used, the methods they used, and the results they achieved.

2. Handwriting Analysis in Parkinson’s disease

The majority of Parkinson's disease (PD) patients have abnormal handwriting. The most frequently reported and easily observable handwriting abnormality in PD patients is micrographia (abnormally small letter size). Micrographia, however, may only be the tip of the iceberg in terms of hand-writing abnormalities in PD. In the past two decades, digitising tablet technology has advanced, making it is possible to research the pressure and kinematics of handwriting. This has led to an increase in studies looking into graphomotor impairment in PD patients **[31].**

3. The impact of Parkinson’s disease on handwriting

- Handwriting can be affected by the restricted, slow movements that people with PD frequently exhibit, which can affect many daily activities. A person with Parkinson's disease (PD) frequently has micrographia, or minuscule and squished handwriting **[32].**
- A person with Parkinson's disease (PD) may also struggle with motor planning, which makes it difficult for them to follow the right steps to make a desired movement. This may also make writing more challenging **[32].**
- Writing and typing can be hampered by the common unwanted movements of PD, such as dystonia, dyskinesia, and tremor **[32].**

4. Related works

4.1. A new modality for quantitative evaluation of Parkinson's disease: In-air movement

In the study **[33]**, a new technique for diagnosing Parkinson's disease was proposed. Experimental results revealed that analysis of airborne trajectory data can be used to identify fine motor abnormalities associated with PD. However, we could generate a predictive model with 80% classification accuracy by correlating airborne trajectory data with surface handwriting. Regarding the dataset and methods used, they are described as follows:

Parkinson's dataset:

38 age-matched healthy controls (20 men and 18 women) and 37 patients with Parkinson's disease (19 men and 18 women) participated in this study. The subject was instructed to write the phrase "Tramvaj dnes u nepojede" (The tram won’t go today) in their home tongue of Czech. X-Y and pressure axis handwritten signals were captured using the digitizing tablet Intuos 4M (Wacom technology) **[33]**.

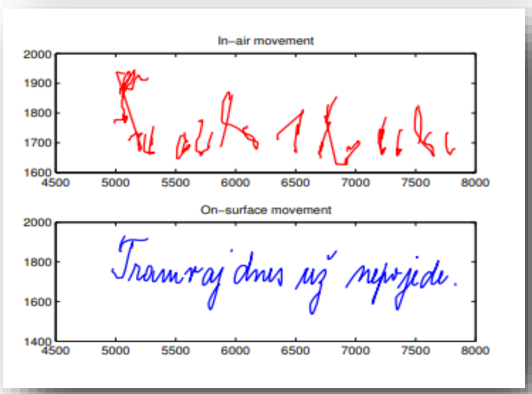


Figure 2. 2:Handwriting sample of PD patient [33]

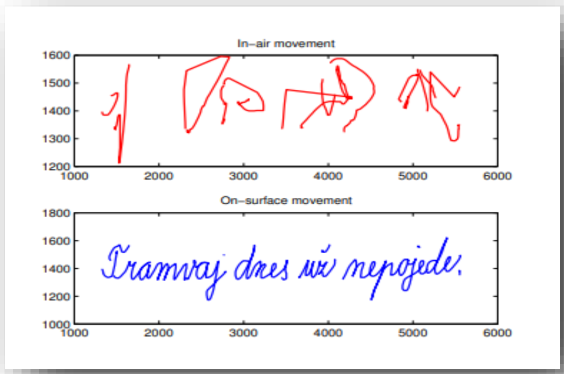


Figure 2. 1:Handwriting sample of healthy control [33].

For the PD prediction challenge, in-air trajectories during writing were used in addition to normal on-surface handwriting. According to the results, unique in-air characteristics perform better than traditional on-surface features at differentiating between PD cases and healthy controls. For the purpose of quantitative recording for the treating physician in order to detect and anticipate long-term changes in the individual illness history, the combination of both modalities can be utilised to build a predictive model **[33]**.

They calculated more than 600 linear features in all. Then, using two feature selection methods, they choose a smaller subset of these features: Support vector machines are used to transform these feature subsets into binary classification responses using the relief algorithm and the Mann-Whitney U-test filter **[33]**.

4.2. Analysis of in-air movement in handwriting: A novel marker for Parkinson's disease

The study **[34]** took advantage of the fact that handwriting movement involves not only hand motions on a surface but also airborne trajectory formation as the hand goes from one stroke to the next.

37 medication-treated PD patients and 38 age- and sex-matched healthy controls were tested using a digital tablet device to measure both air and surface kinetic factors while writing a phrase **[34]**.

Evaluation of hand motions in the air or on a surface led to correct diagnoses in 84% and 78% of respondents, respectively, according to feature selection algorithms and SVM learning methods used to distinguish PD patients from healthy controls. Using both modalities together resulted in a medically meaningful diagnosis with a prediction accuracy of 85.61%, an additional 1% improvement over just evaluating in-air features **[34]**.

4.3. Evaluation of handwriting kinematics and pressure for differential diagnosis of Parkinson’s disease

In this work **[35]**, the researchers want to show how handwriting pressure features and kinematic factors may be used to differentiate between Parkinson's and other diseases.

The database used is the Parkinson's Disease Handwriting PaHaW, which contains writing examples from 38 healthy controls and 37 patients with Parkinson's disease who completed eight different writing activities. Drawing an Archimedes spiral, repeatedly writing simple words and syllables, and creating whole sentences are among the exercises. In addition to conventional kinematic variables associated with handwriting dynamics, we looked at unique pressure features depending on the pressure applied to the writing surface ***[35].***

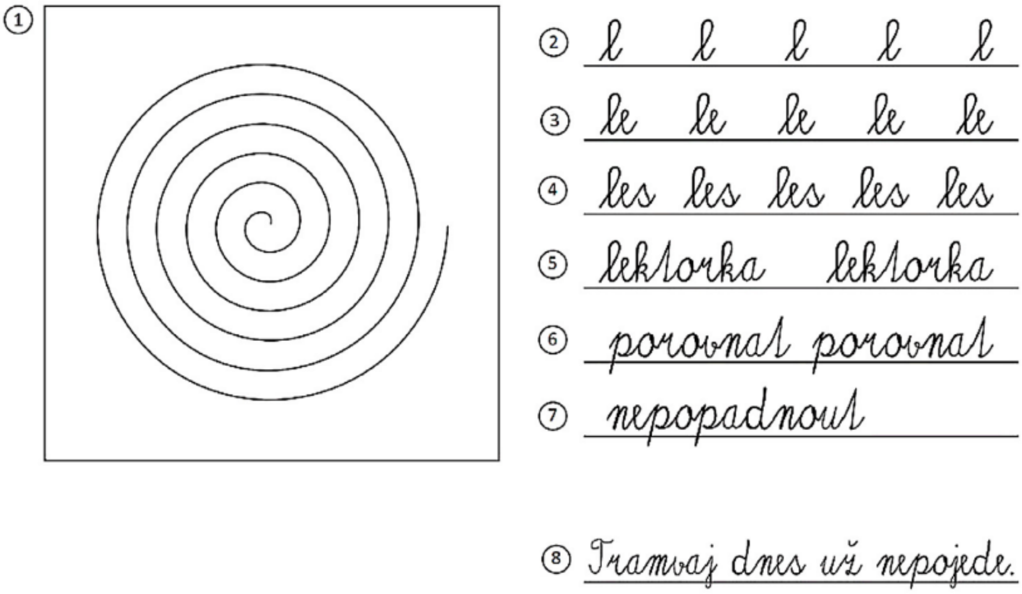


Figure 2. 3: Illustration of filled template (not actual handwriting samples) [35]

They compared K-Nearest Neighbors (K-NN), the AdaBoost group classifier, and support vector machines as three different classifiers to identify PD patients from healthy people.

The findings of predicting PD using the kinematic and barometer properties of handwriting are displayed in the following **Figure 2.4 [35]**:

Classifier	P_{acc} [%]	P_{spe} [%]	P_{sen} [%]
SVM	81.3	80.9	87.4
AdaBoost	78.9	79.2	82.4
K-NN	71.7	70.8	78.5

Figure 2. 4: Comparison of different classifiers for diagnosis of Parkinson's disease from hand writing. Kinematic and pressure features obtained from tasks 2 to 8 were use [35]

With a classification accuracy of P_{acc} = 81.3% (sensitivity of P_{sen} = 87.4% and specificity of P_{spe} = 80.9%), the SVM was the model that performed the best. Pressure features have been demonstrated to be pertinent to the diagnosis of Parkinson's disease when assessed individually, yielding a P_{ACC} = 82.5% as opposed to a P_{acc} = 75.4% when using kinematics **[35]**.

4.4.Anew computer vision-based approach to aid the diagnosis of Parkinson's disease

The difficulty of identifying Parkinson's illness is addressed in this research by fusing machine learning and computer vision methods. Their key contributions are the creation of a new data collection with pictures of spiral and meander patterns that were extracted from handwritten digital examinations. They have also proposed a pipeline to address the issue of learning from unregistered photos. From each test, the suggested method may automatically extract the model and handwritten tracking for use in future feature extraction and classification **[41].**

Their job does not require user involvement because both the template and the images are automatically recognized and segregated using image processing technologies. Given that they lack registered images **[41].**

The dataset was also used for 'HandPD', and the results revealed that very reasonable discrimination (67%) could be obtained, with the patients representing the most accurate group and correctly identifying the controls in the proposed dataset. With a score of 66,74% in the slalom challenge, the SVM classifier is the absolute best **[41].**

Using computer vision and machine learning techniques, the suggested strategy is appropriate to help with the automatic diagnosis of Parkinson's disease. Meander pictures also play a significant role and provide a higher resolution than spiral images. They also noted that the primary obstacle to diagnosing PD is the presence of early-stage patients who can draw nearly perfect things that are very comparable to those created by control patients **[41].**

4.5. Feature Selection for an Improved Parkinson’s disease Identification Based on Handwriting

Since Parkinson's disease identification is challenging, researchers have sought to create a tool that can distinguish between healthy controls and PD patients based on algorithms. One of the techniques for diagnosing PD is online handwriting analysis. The objective of this study is to uncover a subset of handwriting characteristics that can effectively identify people with PD **[36].**

The Lebanon-based PDMultiMC database, which included 16 patients with Parkinson's disease who were taking medication and 16 healthy controls. Seven writing assignments, including writing entire names and Arabic words and patterns, were gathered. Each of the seven handwriting challenges yielded the extraction of motion, stroke, pressure, entropy, and intrinsic properties. Additionally, Parkinson's disease was identified using these several tasks. Feature selection was done in two stages: the first stage used statistical analysis to identify a subgroup, and the second stage used a less than ideal method to identify the features that were most important to that subgroup approach **[36]**.

Figure 2. 5:Handwriting samples (in red). Extracted segments are enclosed in blue boxes [36]

A vector machine classifier with an RBF kernel was fed a set of features in an effort to identify people with Parkinson's disease. With sensitivity and specificity of 93.75% and 100%, PD classification accuracy reached 96.875%. The findings and the traits that were found suggest that handwriting can be an effective diagnostic marker **[36].**

Performance	1 stage Feature selection	2 stages Feature selection
Accuracy (%)	90.625	96.875
Sensitivity (%)	81.25	93.75
Specificity (%)	100	100
AUC	0.4727	0.5938

Figure 2. 6 :Comparison [36]

With a prediction accuracy of 97% when employing a combination of motor-tension relationship characteristics, the findings demonstrate that handwriting can be a technique for detecting Parkinson's disease. In this study, Parkinson's disease patients engaged in handwriting activities while receiving medication. The grading procedure may be impacted by medication side effects on a patient's mobility **[36].**

4.6. Reliable Parkinson’s Disease Detection by Analyzing Handwritten Drawings: Construction of an Unbiased Cascaded Learning System Based on Feature Selection and Adaptive Boosting Model

At this time, there is no test that can conclusively determine whether a patient has Parkinson's disease. The handwriting of Parkinson's patients does, however, appear to deteriorate over time. Techniques based on computer vision have been proposed by numerous researchers in the fields of computer vision and machine learning. However, these methods have two significant issues, particularly when using the HandPD dataset **Figure 2.7 [37].**

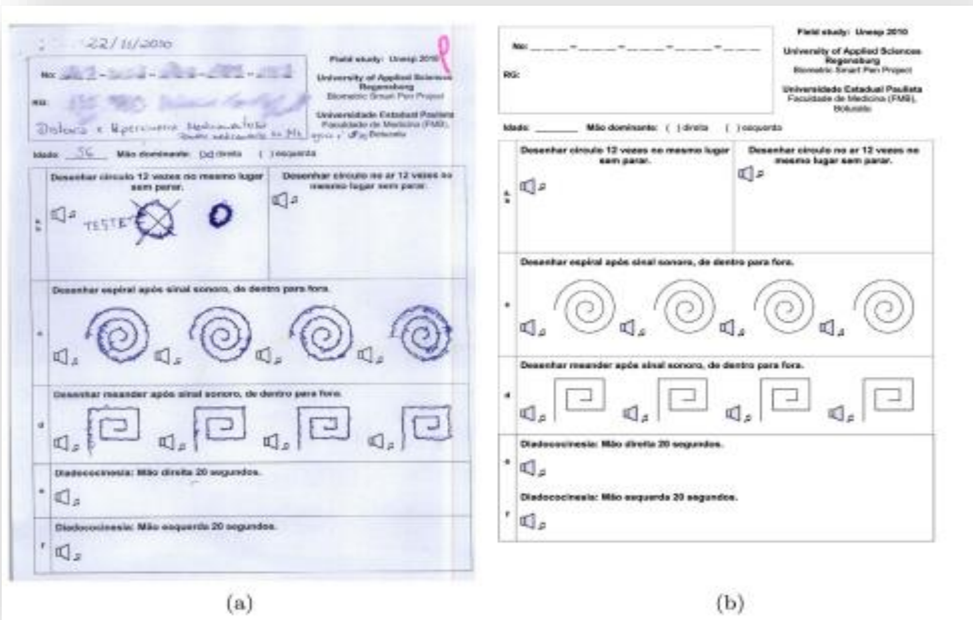


Figure 2. 7:Sample of a form filled by a 56 years old PD patient (a) and sample of an empty form (b).[37]

The first problem is model bias caused by unbalanced data, where machine learning models perform well for the majority class but poorly for the minority class. Unfortunately, previous research has not addressed this problem or suggested any solutions. They created four different machine learning models to highlight bias in the models and prove it empirically. They proposed employing the random sample approach to balance the training process in order to lessen the issue of bias **[37].**

The second problem is the poor categorization accuracy rate, which has little clinical impact. Machine learning techniques were combined with feature selection methods to increase the accuracy of PD identification. As a result, the cascaded learning system known as Chi2-Adaboost was created **[37].**

In contrast to the Adaboost model, which predicts PD based on a selection of features, the Chi2 model classifies and narrows down a subset of pertinent features from the feature space. It was demonstrated that the suggested system performed better than six comparable cascaded learning systems. It was also noted that the performance of a traditional Adaboost model was enhanced by 3.3% by the proposed cascaded method **[37].**

Method	S	ACC_{bal}	Sen(%)	Spec(%)	F	MCC
Chi2-GNB	5	68.97	71.28	66.66	0.794	0.313
Chi2-DT	4	65.09	63.51	66.66	0.740	0.242
Chi2-LDA	7	74.00	84.12	63.88	0.872	0.438
Chi2-KNN	3	63.85	65.20	62.50	0.748	0.224
Chi2-SVM(Lin)	4	58.65	27.02	90.27	0.417	0.161
Chi2-SVM(RBF)	1	54.52	11.82	97.22	0.210	0.119
Chi2-Adaboost	**8**	**76.44**	**70.94**	**81.94**	**0.809**	**0.429**

Figure 2. 8:Performance of the proposed cascaded system on meander data using 4-fold cross validation.[37]

Nevertheless, in this work, the issue of bias in the created models was avoided, and an unbiased cascade model was established that increases the accuracy of PD detection and decreases the complexity of machine learning models by lowering the number of features. However, a classification accuracy of 76.44%, sensitivity of 70.94%, and specificity of 81.94% were reached by the cascade system. As a result, the accuracy attained needs significant improvement **[37].**

4.7. Refining Parkinson’s Neurological Disorder Identification Through Deep Transfer Learning

Deep learning is utilised in this study to find issues with Parkinson's illness. They also advised defining PD as a non-invasive strategy using handwritten images. They suggested a deep convolutional neural network classifier for this use, along with transfer learning and data augmentation methods to enhance selection. Using the ImageNet and MNIST datasets as independent sources, two transfer learning strategies—freeze and fine-tuning—are examined **[38].**

In order to improve the diagnosis of Parkinson's disease, they proposed an AlexNet classifier with transfer learning technology to find handwriting impairment in Parkinson's patients. Since there are not many samples, the basic concept is to model handwriting attributes from AlexNet and apply them to their target data. Therefore, the pre-trained Alexnet-ImageNet and AlexNet_MNIST were employed. Using two independent source datasets (MNIST and ImageNet), they investigated the two widely used methods of learning transfer (freezing and fine tuning). Using ImageNet has been rigorously shown to be an effective feature extraction method that outperforms the latest systems.

To evaluate their proposed investigations, they used the PaHaW database (Parkinson's Disease Handwriting). They include handwriting samples taken by Drutterer using digital discs from 38 **[38].**

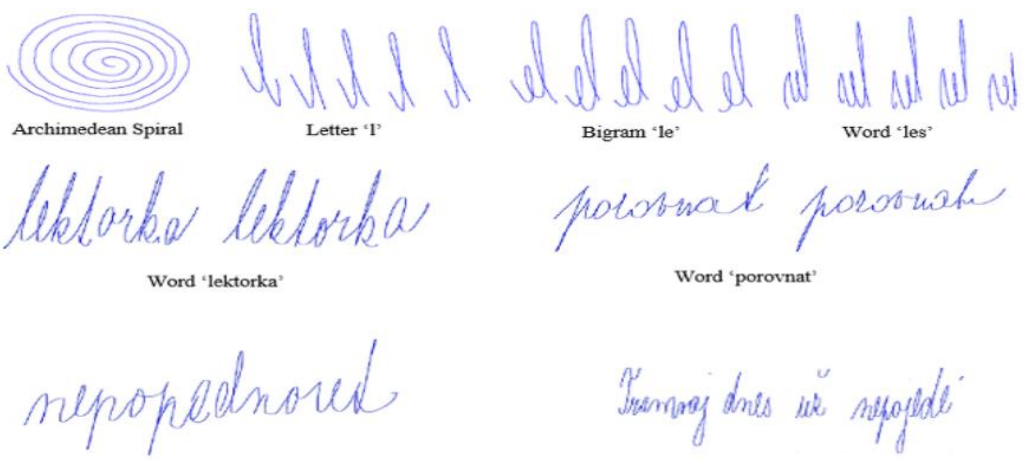


Figure 2. 9:An example of samples of PaHaW dataset [38]

healthy people and 37 patients with Parkinson's disease. However, many of the participants did not finish their tasks according to the samples provided, and thus the samples of these participants were discarded. We have 576 samples from 72 participants (36 PD and 36 controls) after exclusion.

PaHaW collects data using a digital disc, so instead of images, it consists of various online variables such as the (x, y) coordinates of the pen trajectory and the state of the pen (whether or not it touches the writing surface). The use of the PaHaW, a dataset made up of many tasks (tasks 1–8) completed by the same subject, was mainly motivated by the need to collect additional information from different samples done by the same subject. The first activity involves spiral drawings because they are a continuous linear sample and are best suited for evaluating a motion problem. A complete sentence, simple words, and a recurring cursive "l" are among the additional customizations. Figure 2.9 shows an example of a sample data set. The description and statistics of the dataset are shown in Figure 2.10. The PaHaW dataset was divided into a training and test set to assess how well their proposed methodology worked **[38].**

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

Figure 2. 10:The PaHaW dataset description [38]

Using a method based on fine-tuning with the ImageNet and PaHaW datasets, a trained network attained 98.28% accuracy on spiral patterns. According to experimental findings using a benchmark dataset, the suggested technique performs better at detecting Parkinson's disease than current best practises. Here is a summary of the benefits of the proposed deep learner classifier **[38].**

- The performance of the proposed classifier is greatly improved by its ability to automatically extract hidden features.
- The proposed classifier allows remote diagnosis and monitoring of Parkinson's disease. As a result, patients rarely need to go to the clinic.
- The results indicate that the proposed classifier is superior to the traditional methods, which makes the deep learning classifier a trustworthy classifier for PD.

We concluded from the proposed study that spiral images are more useful in detecting Parkinson's disease than letters, words, and phrases. Although the PaHaW dataset has fewer spiral patterns than we can add by augmenting the data, a combination of multiple spiral datasets is thought to be more effective in detecting Parkinson's disease **[38].**

4.8. Results of Related works

Study	**Dataset**	**APPROACH**	ACCURACY
[33]	Parkinson's dataset	SVM	80%
[34]	PAHAW	SVM	85.61%
[35]	PAHAW	SVM	81.3%
[41]	handPD	SVM	66.72%
[36]	PD MULTI MC	SVM	96.87%
[37]	handPD	Chi2 - Adaboost	76.44%
[38]	PAHAW	ALEXNET	98.28%

Table 2. 1:Results of related works

5. Conclution

As a result of the foregoing, we draw the conclusion that the handwriting relationship with Parkinson's disease is very significant in early diagnosis, so handwriting analysis can be used as a useful tool to detect Parkinson's disease and track its progression, but it cannot be regarded as a last-resort method for Parkinson's disease. As we looked at the data set, the techniques used, and the outcomes obtained, we discovered that handwriting analysis is only regarded as an integrative tool for medical diagnosis.

PART TWO

PRACTICAL STUDY

CHAPTER 03

EXPERIMENTAL IMPLEMENTATION AND RESULTS

I. Introduction

Along with the work procedures, we have included a comprehensive description of the methodologies and tools used in this chapter. We next used the Parkinson's disease dataset under the appropriate ergonomics and also touched on the working structures of the learning transfer techniques we used (vgg16 and vgg19). In addition, we used a series of procedures that included split datasets, pre-processing, confusion matrix training, and evaluation of specific models.

II. Part one: Transfer learning and action steps

In this work, we used transfer learning and worked on two previously mentioned models, vgg16 and vgg19. The working methods of these two models consist of a series of steps that occur in order (see **Figure 3.1)**. We delve more into each of them below.

1. Transfer Learning

Transfer learning enables the use of pre-trained networks for novel use cases, which may be advantageous in terms of resource conservation and increased efficiency. Transfer learning's main goal is to use previously learned information to solve new problems involving various types of data. Because a new model doesn't need to be trained from scratch, transfer learning also saves a lot of training time. When there is not enough data, this strategy is equally successful. It enables the user to use a fully fresh dataset to address entirely unique issues. It enables the user to select the last layer's dimensions as desired. Additionally, users can fine-tune various hyperparameters and weights in the other layers of the pre-trained model using the transfer learning approach, in addition to changing the dimensions of the output layer. In transfer learning, the last layers are often movable, while the initial layers are permanent or locked and hard to change **[39].**

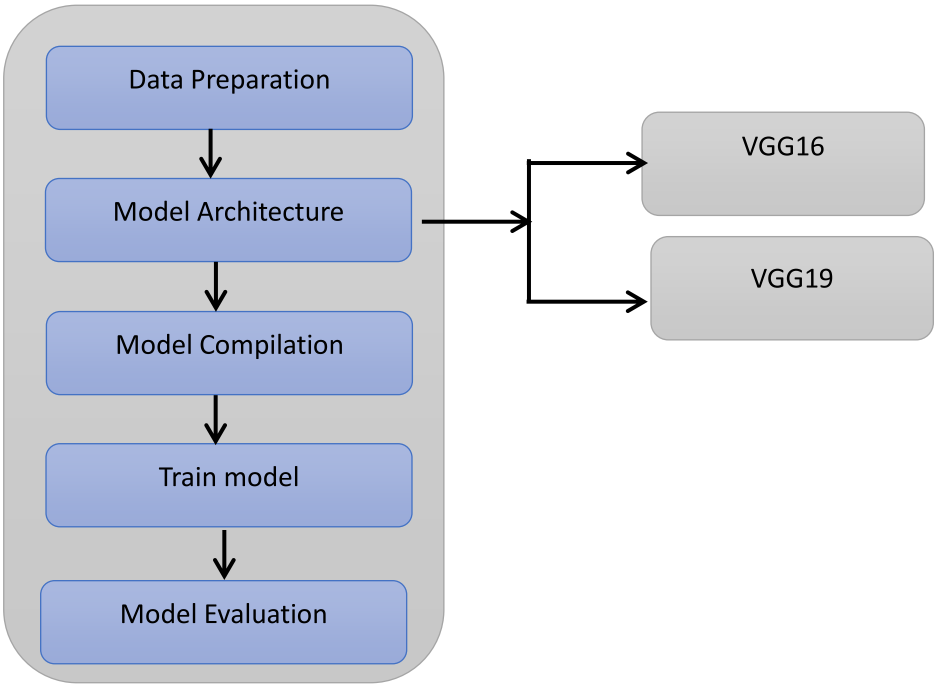


Figure 3. 1:Action Steps

2. Action Steps

2.1. Data Preparation

In this step, we first load and process the dataset and then divide it into training and validation sets.

2.1.1. Data set used

We used three widely available PD handwriting datasets in this work: Parkinson's drawing, HandPD, NewHandPD

2.1.1.1. Parkinson's drawing

Handwriting samples 6 make up the Parkinson's Drawings dataset. The dataset comprises two separate picture types—102 spiral samples and 102 wave samples—in the training and testing groups. 51 samples from each of the 102 photos in each category came from PD patients, and 51 samples came from healthy volunteers **[40].**

2.1.1.2. HandPD

The HandPD dataset was obtained at the Botucatu Faculty of Medicine, So Paulo State University, Brazil. It is made up of images extracted from handwriting exams of 92 individuals separated into two groups as follows: The primary group contains 18 exams of healthy people, known as the control group (Healthy Group), and the second group contains 74 exams of Parkinson's disease patients, known as the patient group. Each person is requested to fill out a form in order to complete a task, such as drawing spirals, meanders, and circles, in order to contribute to the dataset, which consists of the repetition of various procedures in accordance with particular drawings. However, the image analysis will concentrate on tasks linked to sketching four spirals and four meanders according to the design. As a result, the total dataset is made up of 736 photos categorised as patients (296) and controls (72). Furthermore, the dataset contains 368 images from drawing spirals and 368 images from drawing meanders **[41].**

Figure 3. 2:exemple de examn [41]

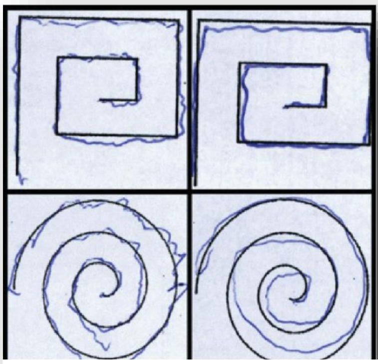


Figure 3. 3:Examples from spiral and meander classes of the patient group [39]

Patient Group: 15 female and 59 male people ranging in age from 38 to 78 years old (average age of 58.75±7.51 years). Five (5) of those people are left-handed, and 69 are right-handed **[41].**

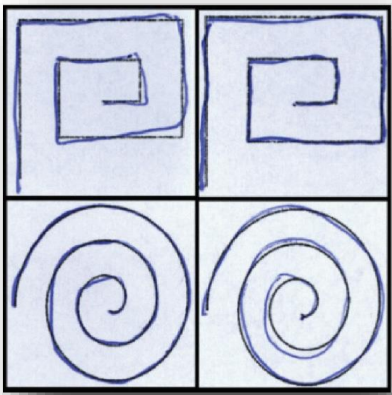


Figure 3. 4:Examples from the spiral and meander classes of the control group [39]

Healthy Group (The control group**):** 12 female and 6 male people ranging in age from 19 to 79 years old (average age 44.22±16.53 years). Two (2) of those people are left-handed, while sixteen (16) are right-handed **[41].**

2.1.1.3. **NewhandPD**

The NewhandPD dataset, which consists of 66 people split into two groups, The first group comprises 35 individuals called healthy, and the second group consists of 31 individuals called patients. This is an upgraded version of the HandPD dataset. Each person was requested to draw 12 exams: two circling motions (one in the air and one on the paper), four (4) of them involving spirals, four (4) involving meanders, and left- and right-handed diadochokines. During the exam, also captured the handwriting dynamics using a smart pen (BiSP), so we have photos from four meanders, four spirals, and one circle on paper, as well as indications for all exams 12.

In summary, we have nine (9) photos and twelve (12) signals for each individual **[42].** This dataset contains 594 photos divided into 6 groups, three of which belong to healthy persons and the remaining three to Parkinson's disease patients. They are as follows: **[43]**

Groups of datasets NewhandPD	number of images
Healthy Meander	140 images
Healthy Spiral	140 images
Healthy Circle	35 images
Patient Circle	31 images
Patient Meander	124 images
Patient Spiral	124 images

Table 3. 1: number of images in each group[43]

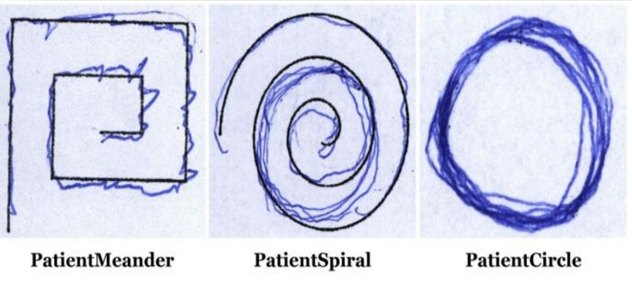


Figure 3. 5:NewHandPD dataset Group Patient [43]

Patient Group: 10 female and 21 male people ranging in age from 38 to 78 years old (average age of 57.83±7.85 years). two (2) of those people are left-handed, 29 are right-handed **[42].**

Healthy Group (The control group**)**: 17 female and 18male people ranging in age from 14 to 79 years old (average age 44.05±14.88 years). five (5) of those people are left-handed, while and 30 are right-handed **[42].**

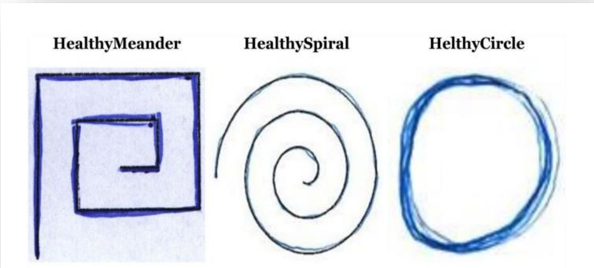


Figure 3. 6:NewhandPD dataset Group Healthy [43]

2.1.2. Pre process

In order to ensure that all of the photographs in the dataset have the same dimensions, we pre-process the images by resizing them to a predetermined size (224, 224).

2.1.3. Split the dataset

The data set was divided into training and validation groups for this study. The average split is 80% trained and 20% validated. As we said before, we have three data sets that we will work on.

2.2. Model Architecture

The visual geometry group (VGG) team won this competition by submitting the VGGNet design for ILSVRC 2014. It is created by extending the depth of the currently existing CNN model up to 16 or 19, respectively, and is known as VGG-16 and VGG-19, **[44]** as illustrated in **Figure 3.7.**

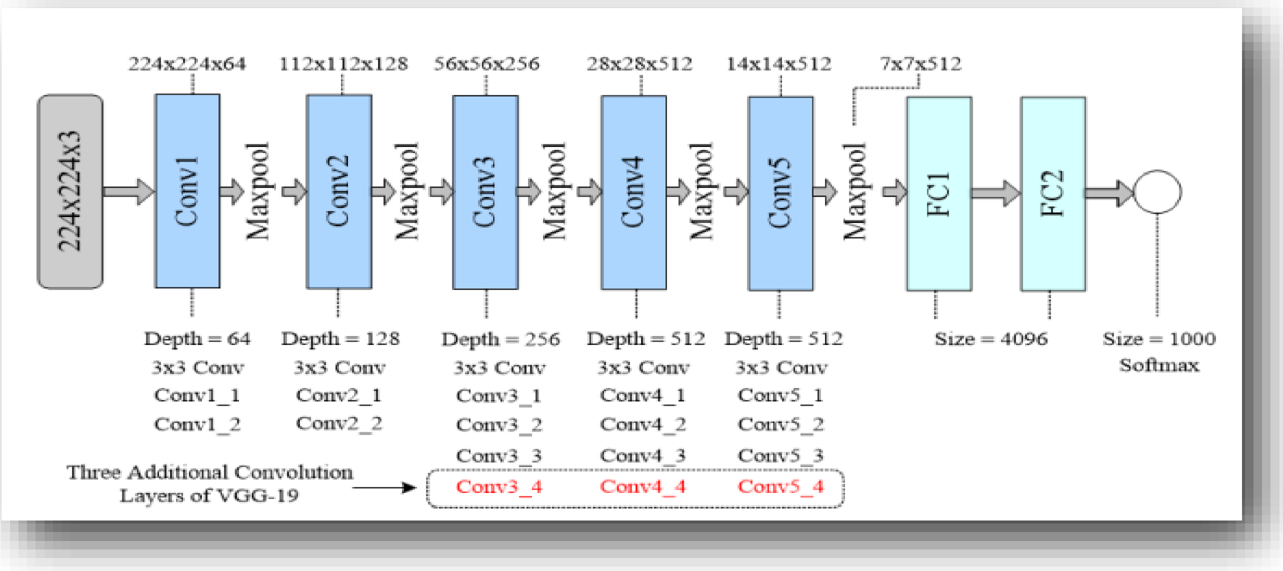


Figure 3. 7: Architecture of VGG-16 and VGG-19[44]

2.2.1. VGG-16

The ImageNet database was used to train the VGG-16 network. The VGG-16 network provides good accuracies even with small picture data sets because of the considerable training it underwent **[45].** There are 138 million parameters in the VGG-16 architecture **[44].** The VGG-16 network includes 16 convolutional layers and a 3-by-3 receptive field. It contains five such levels, each with a maximum pooling layer of size 2 by 2. After the last Max pooling layer, there are three completely linked layers. Three completely linked layers come next. The final layer is the Softmax classifier. All buried layers receive ReLU activation **[45]. Figure 3.8** depicts a schematic of the VGG-16 architecture adopted in this work

```
Model: "model"
_________________________________________________________________
Layer (type)              Output Shape              Param #
=================================================================
input_1 (InputLayer)      [(None, 224, 224, 3)]     0

block1_conv1 (Conv2D)     (None, 224, 224, 64)      1792

block1_conv2 (Conv2D)     (None, 224, 224, 64)      36928

block1_pool (MaxPooling2D)  (None, 112, 112, 64)    0

block2_conv1 (Conv2D)     (None, 112, 112, 128)     73856

block2_conv2 (Conv2D)     (None, 112, 112, 128)     147584

block2_pool (MaxPooling2D)  (None, 56, 56, 128)     0

block3_conv1 (Conv2D)     (None, 56, 56, 256)       295168
```

block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 1)	25089

===

Total params: 14,739,777

Trainable params: 25,089

Non-trainable params: 14,714,688

Figure 3. 8:VGG-16 architecture adopted in this work

2.2.2. VGG-19

VGG19 is another transfer learning model that was taught using ImageNet **[39].** There are 144 million parameters in its architecture **[44].**

The network, which comprises 19 layers, was trained using a variety of characteristics. This network has also been used for computer vision applications, but it excels at other image-related tasks as well **[39].**

The architecture of VGG-19 is identical to that of VGG-16 with the exception of the three extra convolution layers that are included in the Conv3, Conv4, and Conv5 convolution blocks of VGG-19 **[44],** which are seen in **Figure 3.7**, as well as a schematic of the VGG-19 design used in this study in **Figure 3.9**.

Model: "model"

```
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856
```

block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2359808

block5_pool (MaxPooling2D) (None, 7, 7, 512)   0

flatten (Flatten)   (None, 25088)   0

dense (Dense)   (None, 1)   25089

===

Total params: 20,049,473

Trainable params: 25,089

Non-trainable params: 20,024,384

Figure 3. 9: VGG-19 architecture adopted in this work

2.3. Model Compilation

Is a process carried out prior to the commencement of training and after the assertions in a model have been written. It verifies the format, defines the measurements, optimizer or learning rate, and loss function. For training but not for prediction, a compiled model is required **[46].**

2.4. Train model

Before you train our network, we divide it, as we mentioned earlier in (), into 80% training and 20% validation, and we train the two proposed models on epochs = 100 and batch_size = 32.

- **Epoch**

  Every sample in the training dataset gets an opportunity to change the internal model parameters once throughout an epoch. A batch or several batches make up an epoch. The number of "epochs" that the learning algorithm will execute over the entire training dataset is a hyperparameter **[47].**

- **Batch_size [47]**

  The number of samples to process before updating is determined by a hyperparameter called batch size.One or more batches of the training dataset can be divided.

  - ✓ Batch Gradient Descent. Batch Size = Size of Training Set
  - ✓ Stochastic Gradient Descent. Batch Size = 1
  - ✓ Mini-Batch Gradient Descent. 1 < Batch Size < Size of Training Se

- **Iterations**

  The number of iterations required to finish one epoch is the sum of all batches. **[48].**

2.5. Model Evaluation

In this thesis, we now analyse the models based on it using several criteria, such as accuracy, specificity, and sensitivity. These scales are founded on a particular matrix known as the confusion matrix.

2.5.1. Confusion matrix

When an algorithm's output may be categorized as positive or negative, yes or no, a confusion matrix is helpful in assessing performance. There are four cells per table, and each one displays a different combination of expected and actual numbers. The following four outcomes are possible **[49]:**

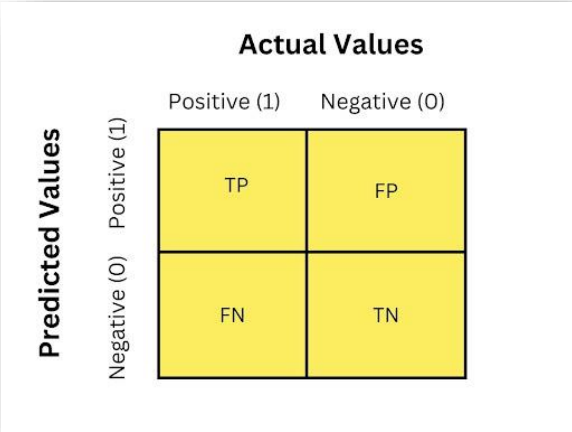


Figure 3. 10:confusion matrix [49]

True Positive (TP): This phrase means that a prediction turned out to be correct. It can also be called sensitivity.

True Negative (TN): This denotes a negative prediction that actually materialized. This quality is known as specificity.

False Positive (FP): Although the value, which was supposed to be positive, actually ended up being negative, Type 1 errors are frequently used to describe them.

False Negative (FN): Despite the value being projected to be negative, it ended up being positive. An error of type 2 is another name for it.

2.5.1.1. Accuracy

The accuracy is the percentage of samples that were classified correctly out of the total samples in the test **[50].**

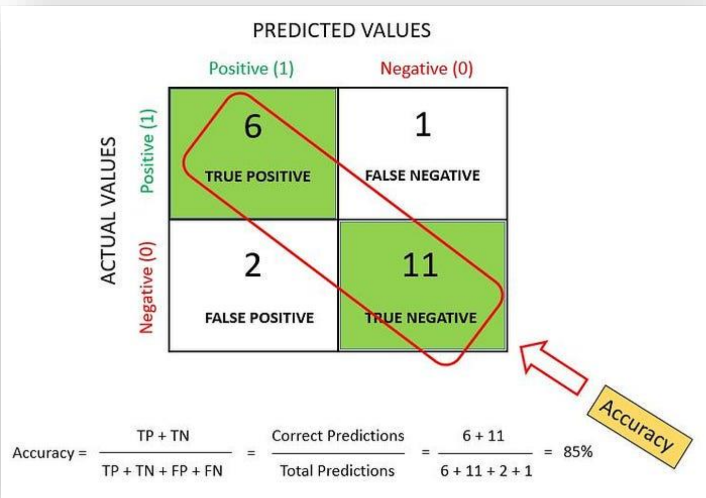


Figure 3. 11:exemple of accuracy [51]

2.5.1.2. Specificity

The percentage of true negative results among all subjects who do not have a disease or condition is known as specificity. In other words, it refers to a test's or instrument's capacity to produce results that are within the normal range or even negative for someone who does not have a disease **[52].** (See **Figure 3.12**)

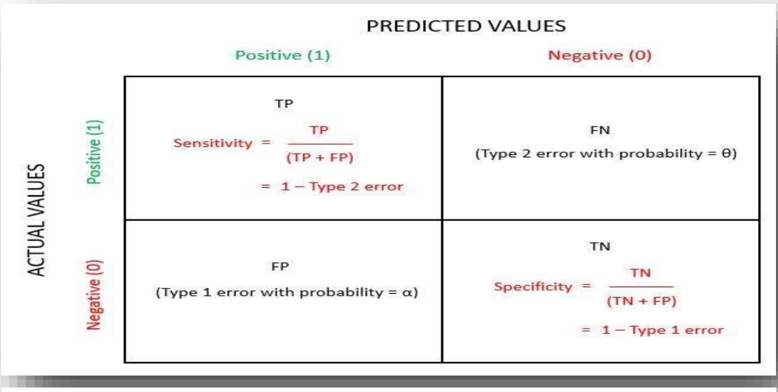


Figure 3. 12 : Sensitivity and specificity [51]

2.5.1.3. Sensitivity

Sensitivity is the percentage of tests that result in true positive results for all patients with a condition. In other words, it refers to the ability of a test or tool to return a positive result for a subject who carries that disease **[52].** (**Figure 3.12**)

III. Part two: The working environment and the tools used

1. Software

1.1. The programming language used

Python is a cutting-edge programming language that supports imperative, functional, and object-oriented programming. Due to its simplicity of usage and ease of reading, it is perfect for beginners. The benefit of this is that programs can be written with fewer lines of code than equivalent Java or C/C++ programs **[53].** It is widely used in the fields of machine learning (ML) and data science due to the strength and breadth of its libraries, including NumPy, Pandas, and Scikit **[54].**

Figure 3. 13:logo of Python [55]

1.2. Anaconda

For scientific computing and data science, Anaconda is a distro of Python and R. It makes it easy to manage dependencies and helps set up a data science environment. There is no end to the installed tools and packages that can be found in the Conda package, Jupyter Notebook,and Spyder IDE **[54].**

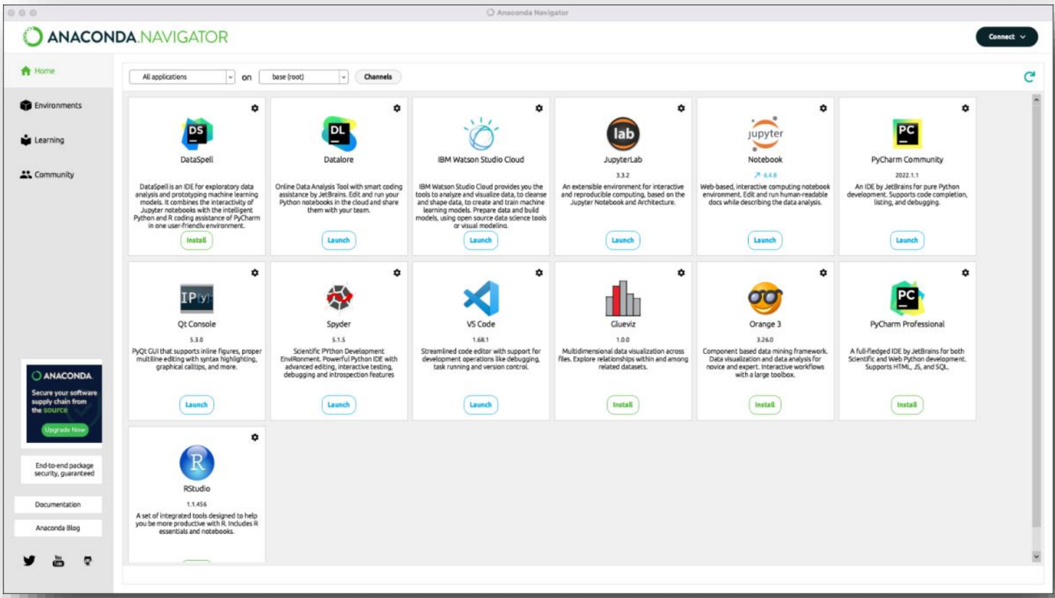


Figure 3. 14: interface of Anaconda [56]

1.3. spyder

Spyder is a robust Python interactive development environment with tools for introspection, interactive execution, advanced editing, and debugging. It was designed to be the most user-friendly, successful, and effective Python IDE. Any sort of developer can use Spyder because it is free and open-source and because it can be used in a variety of ways, including as a Python learning tool, as a lightweight substitute for WingIDEs, as well as other scientific IDEs, and as a complete professional development tool **[57].**

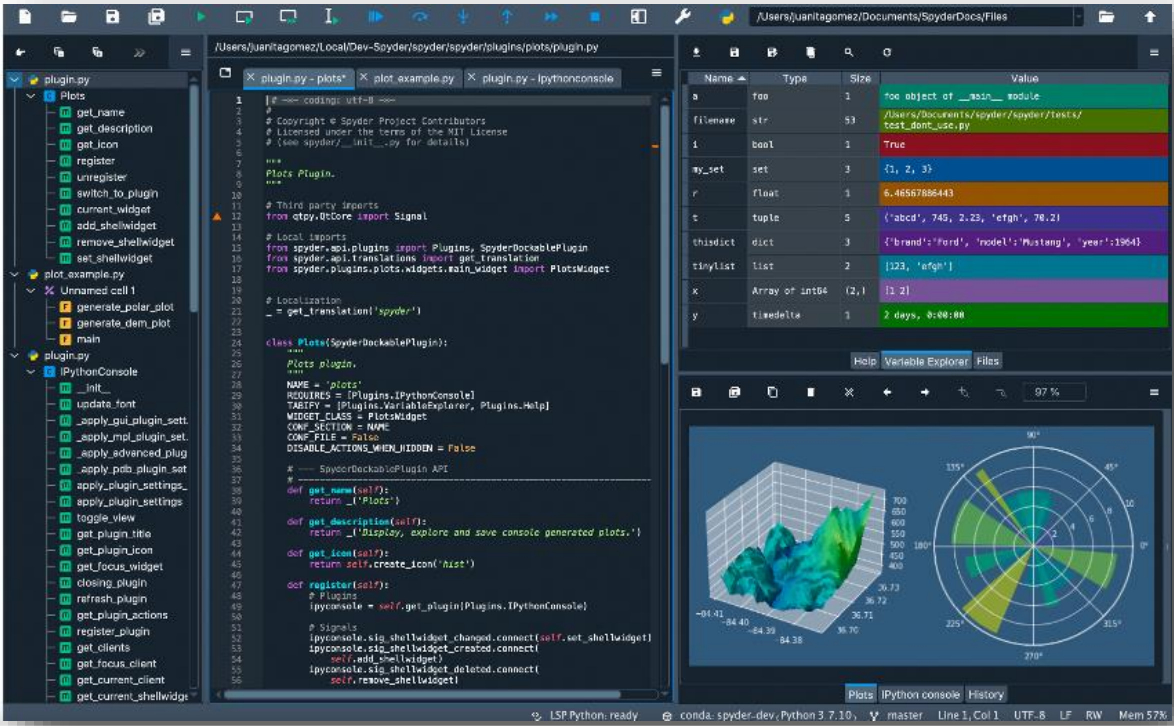


Figure 3. 15:interface of Spyder [57]

2. The libraries used

➢ ***Tensorflow***

Tensorflow is a Google-created open-source software library that enables the creation and execution of data flow graphs for numerical computation. The graph connections connecting the nodes represent the data in multi-dimensional arrays called "tensors" surrounding the graph. Each node in these graphs represents some combination or function to be executed **[58].**

➢ Keras

A deep learning framework for Python called Keras is free software. It was developed by a man by the name of "Francois Chollet," an artificial intelligence researcher. Python was used to provide a top-level neural network API. It supports convolutional and recurrent networks as well as their combinations. Today, several prestigious companies, including Netflix, Google, and Square, use Keras technologies. Using it, deep learning models are produced. Python, C++, and C **[59].**

libraries are among the many programming languages that are used by this system **[59].**

- NumPy

A library called NumPy contains multidimensional array objects and a number of methods for interacting with them. Arrays may be used for mathematical and logical processes, making them one of the most popular Python tools for scientific computing **[60].**

- Opencv

We can create real-time computer vision applications utilizing the cross-platform library known as OpenCV. It largely focuses on image processing, recording, and analysis of videos using software for face and object identification **[61].**

- Pandas

For data analysis and manipulation, the Python programming language's Pandas software library is necessary. In machine learning activities, this open-source software library is frequently utilized. Numpy, another library that supports multi-dimensional layouts, is built into this Python library **[62].**

- Matplotlib

While writing Python programs, users can use the matplotlib module to create two-dimensional graphs and provide features for adjusting coordinate axes and line properties and styles. It works alongside Numpy to provide a Matlab-like environment. WxPython and PyQt are examples of graphics toolkits that can be used **[63]**

- Scikit-Learn (Sklearn)

The most effective and reliable machine learning library in Python is called skean (sckit-learn), and it is a set of various methods that are effective for statistical modeling and machine learning, including classification, regression, clustering, research reduction, etc., as this library written in Python is based on Numpy, Scripy, and Matplotlib **[64].**

3. Hardware Configuration:

This program was created in a type of DELL laptop with the following specifications:

Processor: intel core (TM) i5-8250 Ucp4 @1.60GH 1.8GHz

Installed memory (RAM):8.00 GO

System type: 64-bit operating system

Operating system: Windows 10 pro

IV. Part three: Experimental implementation

At this point, we will apply vgg16 and vgg19 to the three datasets (Parkinson's drawing, HandPD, and NewHandPD) using the previous steps, then extract the results and plot them using the confusion matrix, and then analyze and compare the results.

1. VGG 16

Using the proposed architecture of vgg16(see **Figure 3.8**) and datasets (Parkinson's drawing, HandPD, and NewHandPD) one by one with pre-trained weights (imageNet), we were able to get the following results:

1.1. Dataset Parkinson's Drawing

In the first application of vgg16 on the Parkinson's Drawing dataset, we note that there are good and balanced results in the three forms, but wave is the dominant and balanced one in terms of accuracy, sensitivity, and specificity, which achieved 100% completeness for each one of them As shown in the table (**Table 3.2**).

Parkinson's drawing	Accuracy	Sensitivity	Specificity
WAVE	**100%**	**100%**	**100%**
spiral	80%	66.66%	90%
Spiral +WAVE	90.24%	85%	95.23%

Table 3. 2:Results of Accuracy Sensitivity Specificity Parkinson's Drawing in vgg16

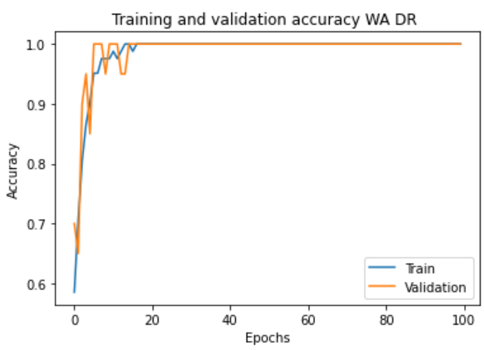


Figure 3. 16:Training and validation accuracy WAVE DrawingVGG16

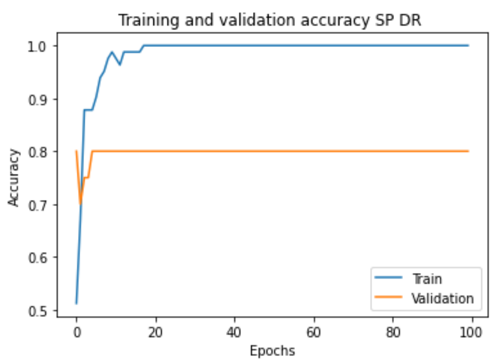


Figure 3. 17:Training and validation accuracy spiral Drawing VGG16

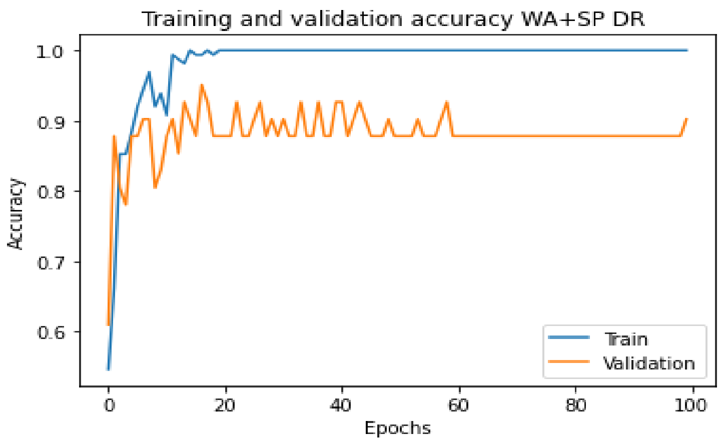


Figure 3. 18:Training and validation accuracy WAVE and Spiral Drawing VGG16

1.2. HandPD

As for the second application of vgg16 on another data set, **HandPD**, we note that both accuracy and sensitivity are high, while the accuracy reached 91.76% in spiral and the sensitivity was 100% in meander. As for specificity, it was acceptable; reaching 66.66% in spiral, but this is partly due to a hand-pd data imbalance, where the number of positive samples is not balanced with the number of negative samples. As shown in the table (**Table 3.3**).

HandPD	**Accuracy**	**Sensitivity**	**Specificity**
spiral	**91.76%**	98.50**%**	**66.66%**
Meander	83.78%	**100%**	57.14%
Spiral + Meander	87.75%	99.04%	59.14%

Table 3. 3:Results of Accuracy Sensitivity Specificity HandPD in vgg16

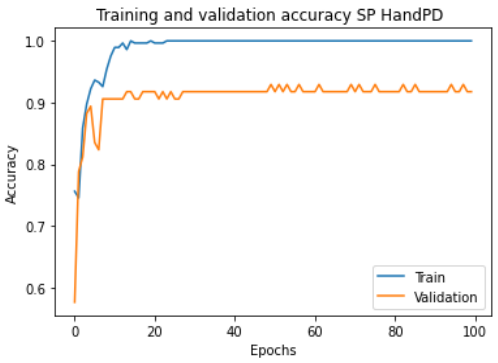


Figure 3. 19:Training and validation accuracy Spiral HandPD VGG16

Figure 3. 20:Training and validation accuracy Meander HandPD VGG16

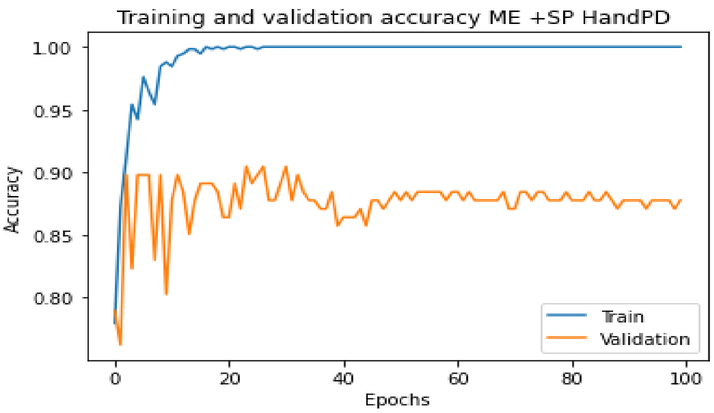


Figure 3. 21:Training and validation accuracy Spiral and Meander HandPD VGG16

NewhandPD

We move to the third type of data set, which is NewhandPD in the vgg16 model, where we note that this group achieved excellent and balanced results better than the other two data sets, and the results reached 100% in each of the accuracy, sensitivity, and specificity of the spiral shape. We also note that all polymorphisms in this group give good results; hence, we found that vgg16 converges towards the spiral task as a reliable test for diagnosing Parkinson's disease. It may also indicate the presence of spirals in the ImageNet (the dataset on which this model was previously trained). As shown in the table (**Table 3.4**).

NewhandPD	Accuracy	Sensitivity	Specificity
Spiral	**100%**	**100%**	**100%**
Meander	94.44%	92%	96.55%
Circle	92.23%	83.33%	100%
Spiral + Meanders	97.19%	96%	98.24%
Spiral + Meander+ Circle	96.66%	94.64%	98.43%

Table 3. 4:Results of Accuracy Sensitivity Specificity NewhandPD in vgg16

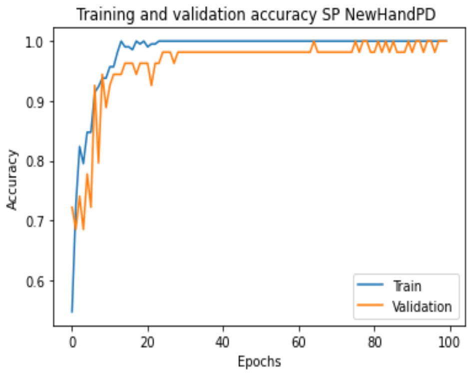


Figure 3. 22:Training and validation accuracy Spiral NewHandPD VGG16

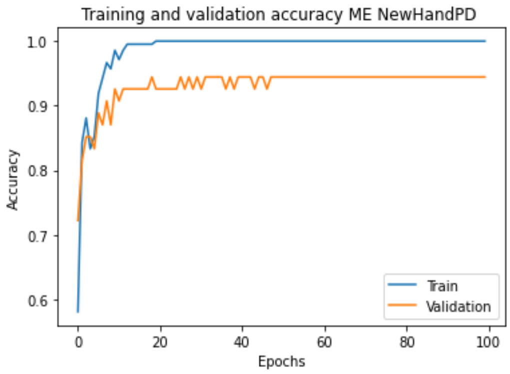


Figure 3. 23:Training and validation accuracy Meander NewHandPD VGG16

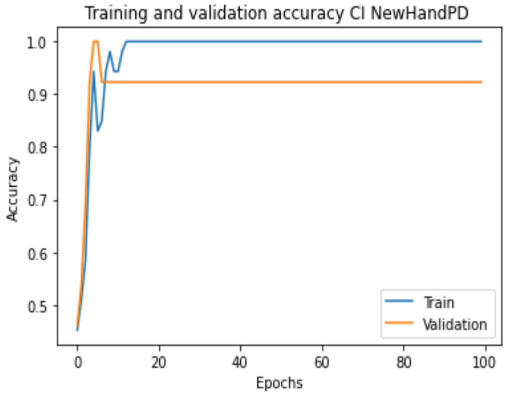


Figure 3. 24:Training and validation accuracy Circle NewHandPD VGG16

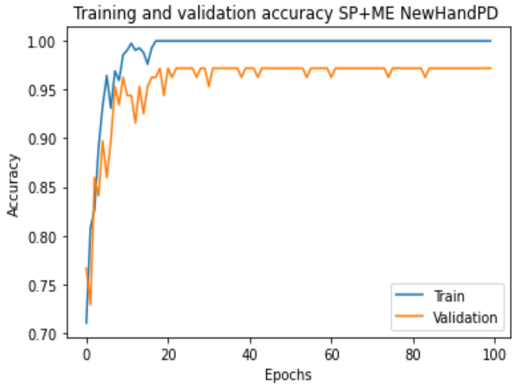


Figure 3. 25:Figure 3. 25:Training and validation accuracy Spiral and Meander NewHandPD VGG16

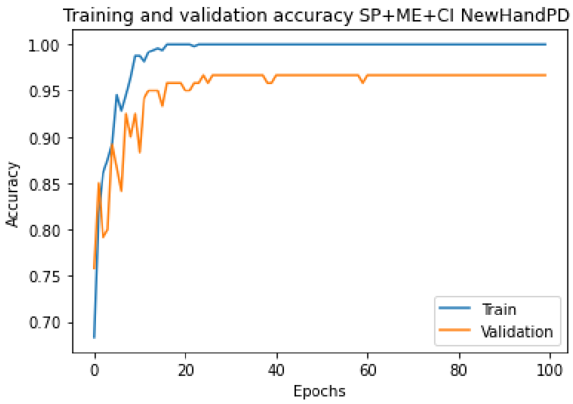


Figure 3. 26:Training and validation accuracy Spiral and Meander and Circle NewHandPD VGG16

2. VGG19

Using the proposed architecture of vgg19 (see **Figure 3.9**) and datasets (Parkinson's drawing, HandPD, and NewHandPD) one by one with pre-trained weights (imageNet), we were able to get the following results:

2.1. Parkinson's drawing

In the first application of vgg19 to the Parkinson's DRAWING data set, we note that the results are convergent, but the wave task was the leader in accuracy, specificity, and sensitivity by 100% for each of them, so it was as balanced as can be. We noticed that the results in vgg16 achieved better results than vgg19 in spiral and wave + spiral. As shown in the table (**Table 3.5**).

Parkinson's drawing	Accuracy	Sensitivity	Specificity
WAVE	**100%**	**100%**	**100%**
spiral	75%	55.56%	90.95%
Spiral + WAVE	87%	85%	90.47%

Table 3. 5:Results of Accuracy Sensitivity Specificity Parkinson's Drawing in vgg19

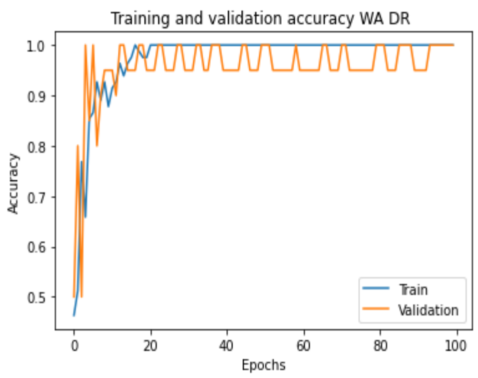


Figure 3. 27:Training and validation accuracy WAVE DrawingVGG19

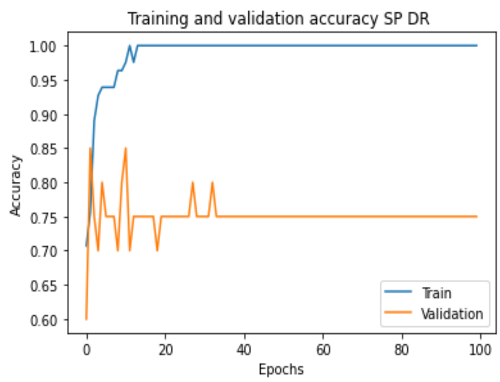


Figure 3. 28:Training and validation accuracy spiral Drawing VGG19

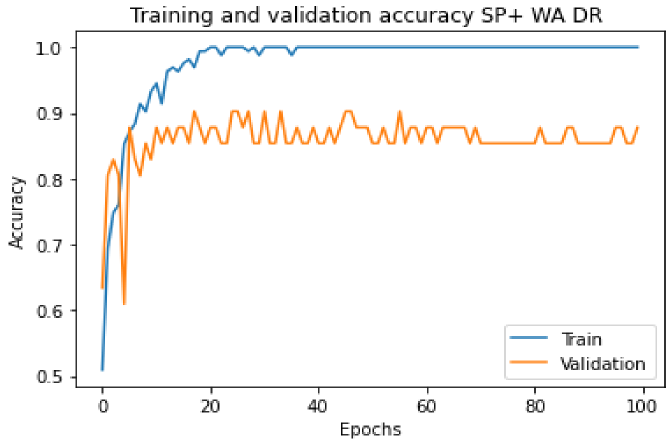


Figure 3. 29:Training and validation accuracy WAVE and Spiral Drawing VGG19

2.2. HandPD

In the second application of vgg19 on the handPD data set, we note that the results obtained in this model are better than those obtained in vgg16. Accuracy and sensitivity reached good results in one type, which is spiral, and we find **Accuracy** = 92.24% and sensitivity = 100%. As for Specificity, it improved relatively only. As shown in the table (**Table 3.6**).

HandPD	Accuracy	Sensitivity	Specificity
Spiral	**92.94%**	**100%**	66.86%
Meander	83.78%	97.82%	60.71%
Spiral + Meander	89.11%	99.04%	64.26%

Table 3. 6:Results of Accuracy Sensitivity Specificity HandPD in vgg19

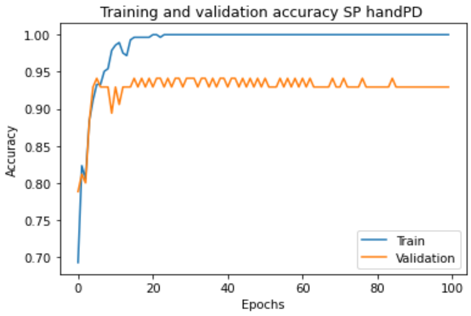


Figure 3. 30:Training and validation accuracy Spiral HandPD VGG19

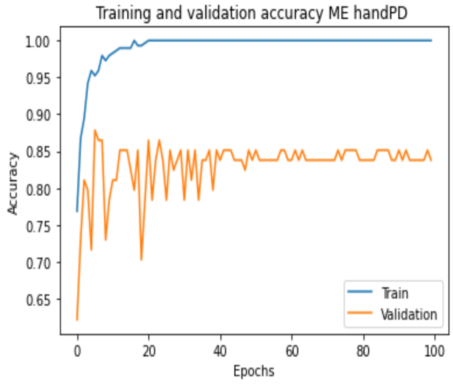


Figure 3. 31:Training and validation accuracy Meander HandPD VGG19

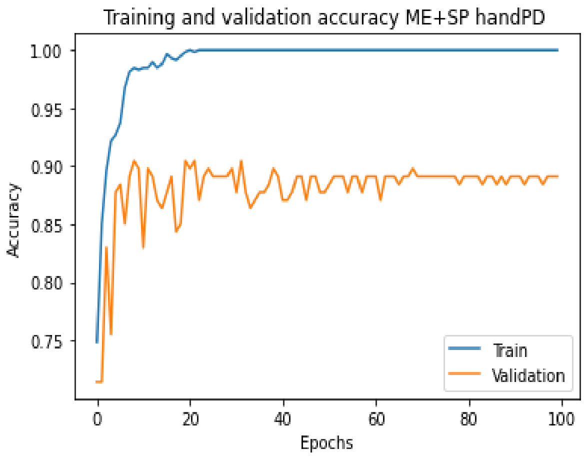


Figure 3. 32:Training and validation accuracy Spiral and Meander HandPD VGG19

2.3. NewhandPD

We move on to the third type of data set, which is NewhandPD in the vgg19 model, where we notice very good and balanced results in all shapes, but the helix is strongly dominant, so its results are perfect, represented by accuracy = 94.44%, sensitivity = 100%, and specificity = 89.65%. As for privacy, it's a good value in the circle we get 100%. Thus, we note that this NewhandPD group achieved excellent results compared to the handPD groups Drawing for Parkinson's disease, and finally, we conclude that vgg16 is better than vgg19 in this dataset. As shown in the table (**Table 3.7**).

NewhandPD	Accuracy	Sensitivity	Specificity
Spiral	**94.44%**	**100%**	**89.65%**
Meander	92.59%	88%	96.55%
Circle	92.30%	83.33%	**100%**
Spiral + Meanders	94.39%	94%	94.73%
Spiral + Meander+ Circle	93.33%	92.85%	93.75%

Table 3. 7:Results of Accuracy Sensitivity Specificity NewhandPD in vgg19

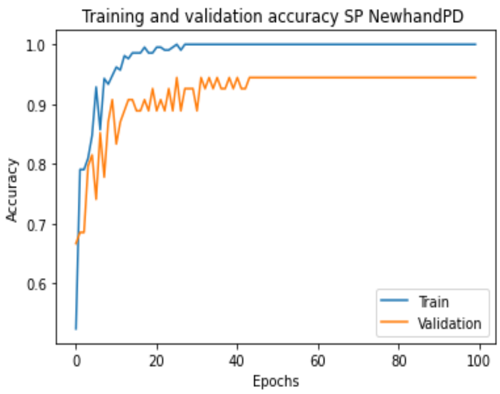


Figure 3. 33:Training and validation accuracy Spiral NewHandPD VGG19

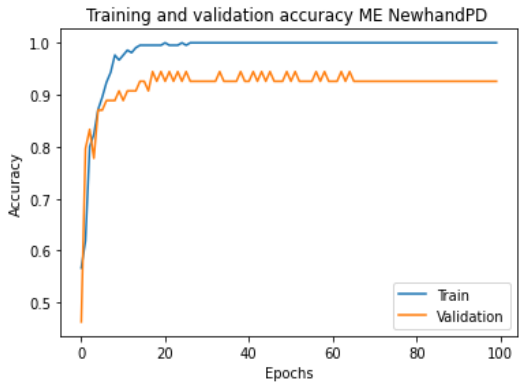


Figure 3. 34:Training and validation accuracy Meander NewHandPD VGG19

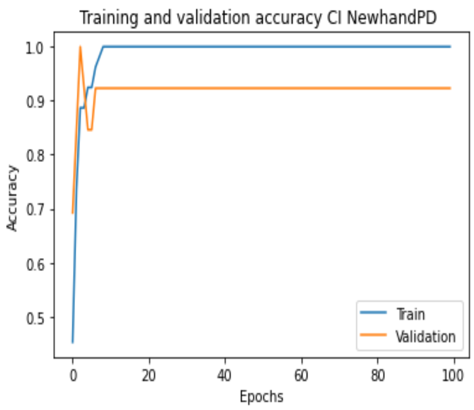


Figure 3. 35:Training and validation accuracy Circle NewHandPD VGG19

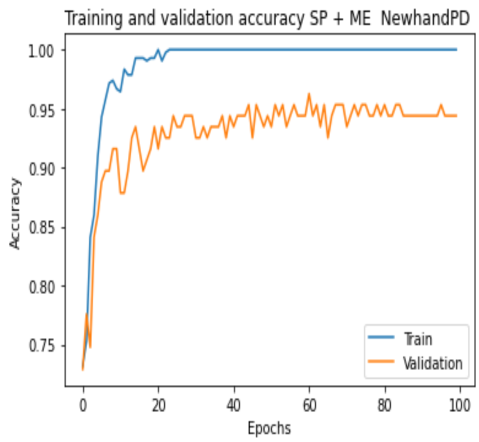


Figure 3. 36:Training and validation accuracy Spiral and Meander NewHandPD VGG19

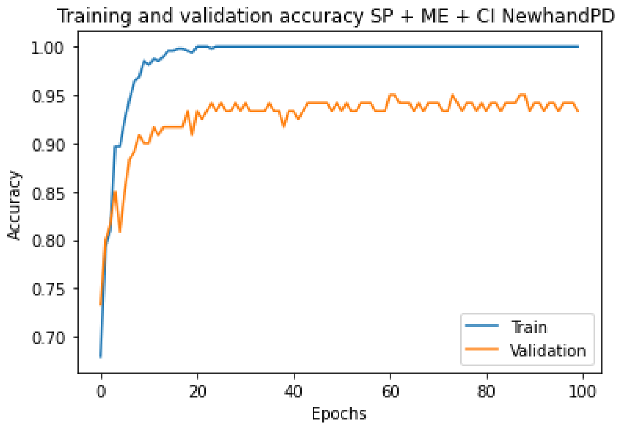


Figure 3. 37:Training and validation accuracy Spiral and Meander and Circle NewHandPD VGG19

V. Conclution

Through what we have discussed in this chapter of the methods and tools used and work environments and our reliance on 3 different evaluation scales (accuracy, sensitivity, and specificity), we can say that transfer learning achieved good results in both types (vgg16 and vgg19) and in three different datasets (Drawing for Parkinson's disease, HandPD, NewhandPD) We also conclude that vgg16 achieved excellent results with 100% accuracy in the spiral task in the NewhandPD dataset. In the HandPD group, vgg19 had a better role than vgg16, achieving 92.24% accuracy in the spiral task. The Drawing Parkinson" dataset saw concordance between the two methods (vgg16, vgg19) with 100% accuracy in the wave task. Ultimately, we say that transfer learning of its two selected types (vgg16 and vgg19) is valid for Parkinson's disease handwriting recognition, especially in the spiral task.

CHAPTER 04

SUGGESTION OF TWO DEEP LEARNING (CNN3, CNN4) FOR DETECTION OF PARKINSON'S DISEASE

I. Introduction

In this chapter, we relied on suggestions of new models, namely ("CNN3.CNN4"), using a Convolutional Neural Network (CNN) only to train and test these models. We followed a set of steps until we got the results, analyzed them with VGG16 and VGG19, and compared them with previous works.

II. Our suggestions

In this work, we will propose two CNN models and then apply the same previous steps that we applied to vgg16 and vgg19

Action steps applied to the two proposed models (see **Figure 3.1, Figure 4.1):**

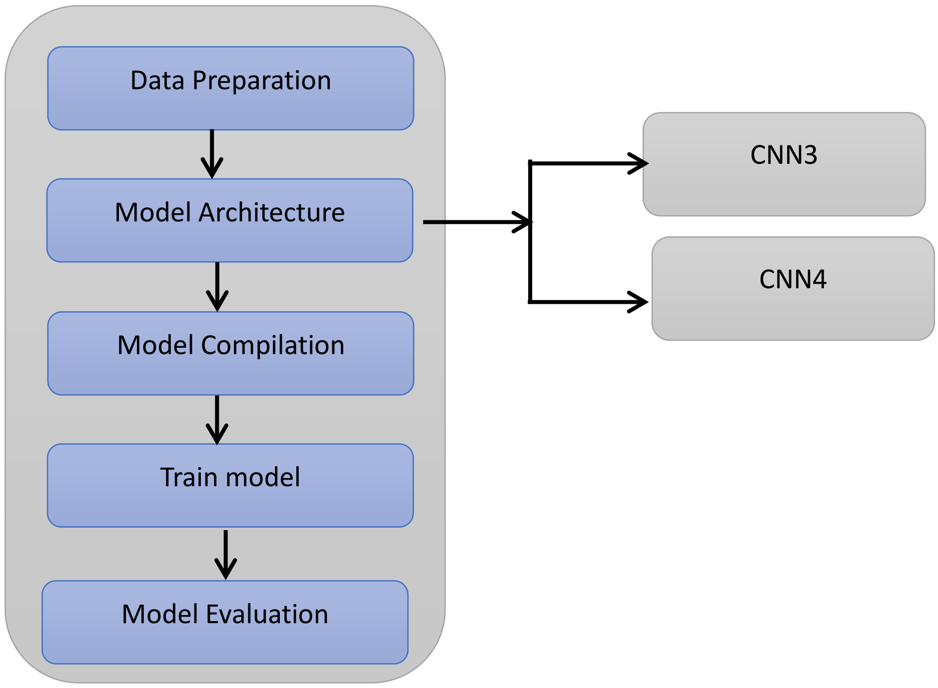


Figure 4. 1:Action steps

1. CNN4

We created a sequential model with 12 layers using the libraries Keras / TensorFlow, including the Conv2D, MaxPooling2D, Dense, and Dropout layers. To enhance the performance of the model, the parameters in these layers are trained during the training process. Sequential order is used to assemble the layers.

2. CNN3

We created a sequential model with 10 layers using the libraries Keras / TensorFlow, including the Conv2D, MaxPooling2D, Dense, and Dropout layers. To enhance the performance of the model, the parameters in these layers are trained during the training process. Sequential order is used to assemble the layers. The Dropout layer is employed to enhance generalisation and avoid overfitting.

III. Application results

1. CNN4

Based on the above CNN4 structure (see **Figure 4.2**) and using the methods and methods in (see **Figure 4.1**), we implement CNN4 on three datasets (HandPD, NewHandPD, and Parkinson's drawing) one by one and get the following results:

1.1. Parkinson's Drawing

In the first application of the CNN4 model to the first set of drawing data, we see that its results are acceptable and balanced, especially in the spiral task. It provided good results, with an accuracy of 90% and a full percentage of 100% in sensitivity. As for its specificity, its percentage was estimated at 81.81%. These results indicate that this model achieved results. Good at data set drawing. As shown in the table (**Table 4.1**).

Parkinson's drawing	Accuracy	Sensitivity	Specificity
WAVE	70%	70%	70%
spiral	**90%**	**100%**	**81.81%**
Spiral +WAVE	73.17%	75%	71.41%

Table 4. 1:Results of Accuracy Sensitivity Specificity Parkinson's Drawing in CNN4

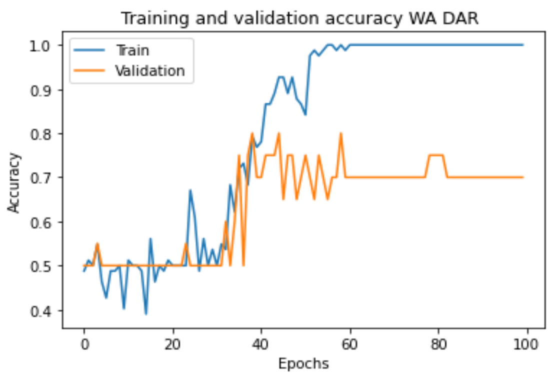


Figure 4. 2:Training and validation accuracy WAVE Drawing CNN4

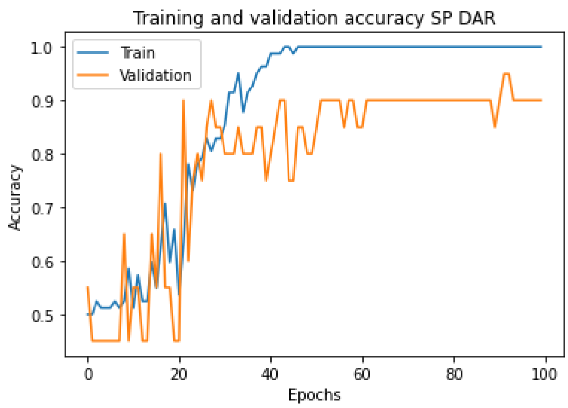


Figure 4. 3:Training and validation accuracy spiral Drawing CNN4

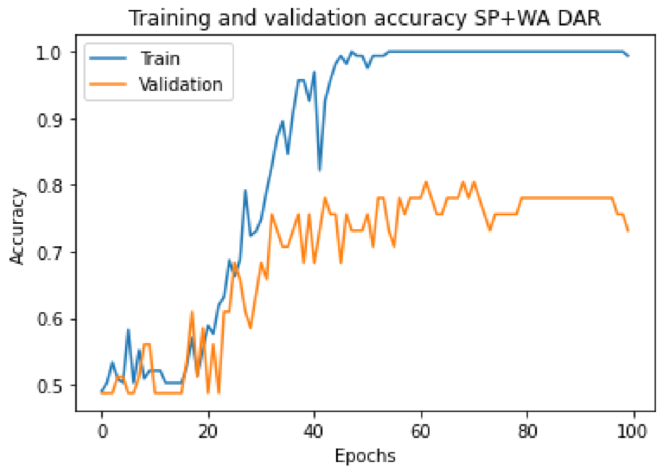


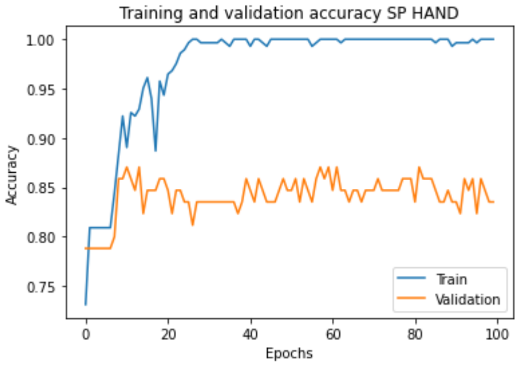
Figure 4. 4:Training and validation accuracy WAVE and Spiral CNN4

1.2. HandPD

In the second application of the CNN 4 model on the second data set, "HandPD", this model achieved similar results, and we also note that both accuracy and sensitivity are close and good, as the accuracy reached 83.52% in the spiral task and in the meander task, the sensitivity was good by 95.65%. However, these results are partially rejectable due to a lack of precision, which is due to the imbalance of the " HandPD " data set. As shown in the table (**Table 4.2**).

HandPD	Accuracy	Sensitivity	Specificity
spiral	**83.52%**	92.53%	**50%**
Meander	72.97%	**95.65%**	35.71%
Spiral + Meander	82.99%	95.23%	52.38%

Table 4. 2:of Accuracy Sensitivity Specificity HandPD in CNN 4



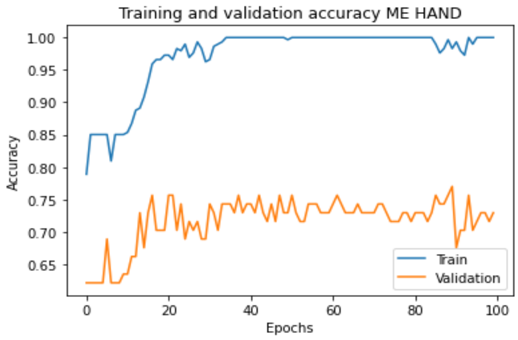


Figure 4. 5:Training and validation accuracy Spiral HandPD CNN4

Figure 4. 6:Training and validation accuracy Meander HandPD CNN4

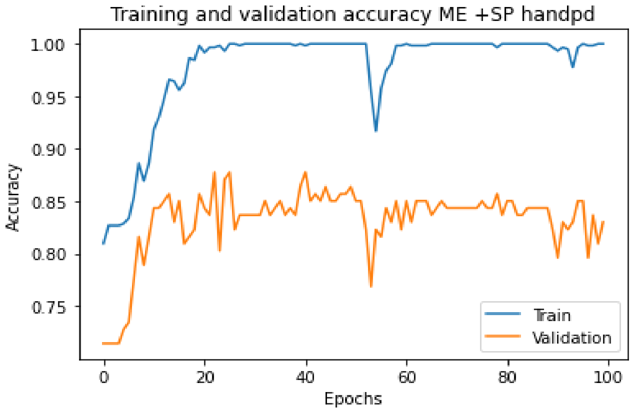


Figure 4. 7:Training and validation accuracy Spiral and Meander HandPD CNN4

1.3. NewhandPD

On the last application of the cnn4 model to the third set of data, NewHandPD, we note that this model performed better in terms of outcomes and balance than a previous set of data (Drawing; HandPD). The accuracy was very close in the two meander tasks, with a ratio of 90.74, and in the meander and spiral, with a ratio of 90.65, while the sensitivity was good in the meander and spiral, with a ratio of 94, and the specificity reached a ratio of 95.31 in the sum of the spiral, meander, and circle As shown in the table **(Table 4.3).**

NewhandPD	Accuracy	Sensitivity	Specificity
Spiral	88.88%	92%	86.20%
Meander	**90.74%**	92%	89.65%
Circle	84.61 %	83.33%	85.71%
Spiral + Meanders	**90.65%**	**94%**	87.71%
Spiral + Meander+ Circle	90%	83.92%	**95.31%**

Table 4 .3Results of Accuracy Sensitivity Specificity NewhandPD in CNN4

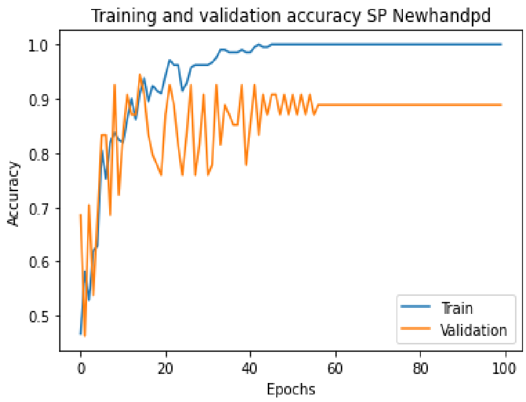
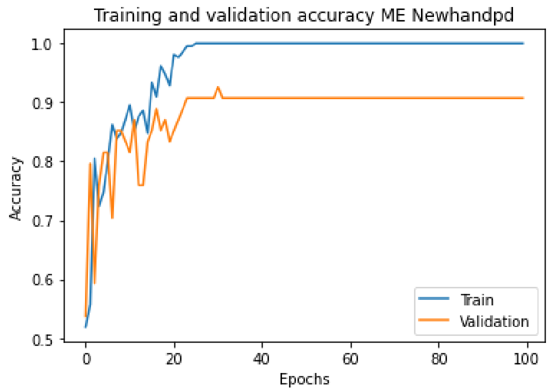
	

Figure 4.8:Training and validation accuracy Spiral NewHandPD CNN4	***Figure 4.9:Training and validation accuracy Meander NewHandPD CNN4***

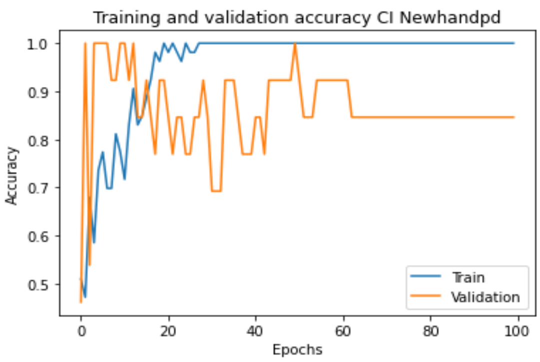


Figure 4. 10:Training and validation accuracy Circle NewHandPD CNN4	***Figure 4. 11:Training and validation accuracy Spiral and Meander NewHandPD CNN4***

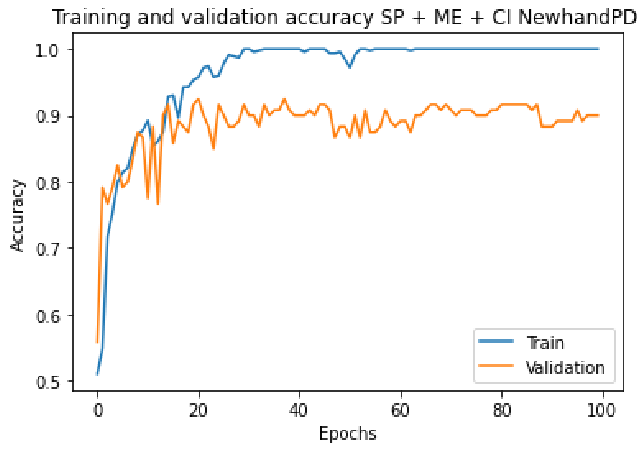


Figure 4. 12:Training and validation accuracy Spiral and Meander and Circle NewHandPD CNN4

2. CNN3

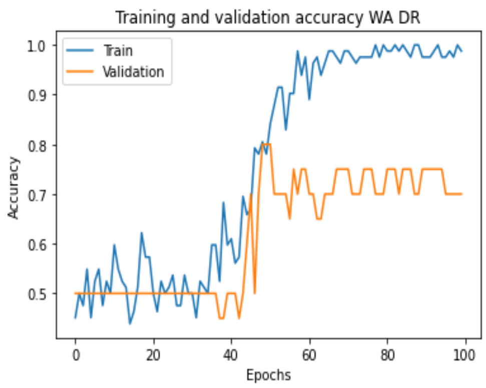
Based on the above CNN3 structure (see **Figure 4.3**) and using the methods and methods in (see **Figure 4.1**), we implement CNN3 on three datasets (HandPD, NewHandPD, and Parkinson's drawing) one by one and get the following results:

2.1. Parkinson's Drawing

In the first application of the CNN3 model on the first data set drawing, we see that its results are close in equal proportions, so it achieved an accuracy of 70% in the spiral and wave tasks, respectively. As for the combination of the spiral task and the wave, it achieved accuracy higher than theirs by 3%, which is approximately 73.17%, with a sensitivity of 60% and a specificity of 85.57%. Finally, we can say that CNN 4 achieved much better results than CNN 3 in the drawing dataset. As shown in the table **(Table 4.4).**

Parkinson's drawing	Accuracy	Sensitivity	Specificity
WAVE	70%	**60%**	80%
spiral	70%	55.55%	81.81%
Spiral + WAVE	**73.17%**	**60%**	**85.71%**

Table 4.4:Results of Accuracy Sensitivity Specificity Parkinson's Drawing in CNN3



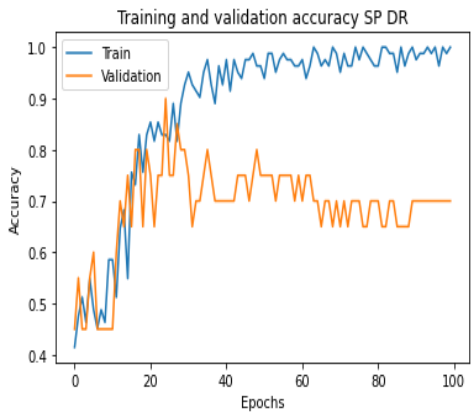


Figure 4. 13:Training and validation accuracy Wave Drawing CNN3

Figure 4. 14:Training and validation accuracy spiral Drawing CNN3

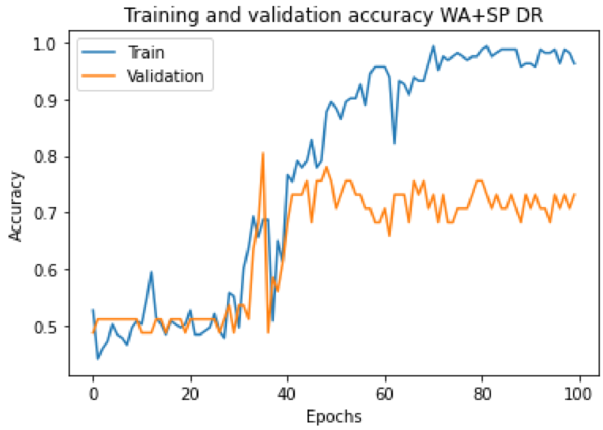


Figure 4. 15:Training and validation accuracy WAVE and Spiral CNN3

2.2.*HandPD*

In the second application of the CNN 3 model on the second handPD data set, this model achieved good and convergent results. It reached 88.23% accuracy and a sensitivity of 94.02% in the spiral task. As for "Meander" and "Spiral + Meander ", their respective accuracy, sensitivity, and specificity were good and increased better than those of CNN4. As shown in the table **(Table 4.5).**

HandPD	Accuracy	Sensitivity	Specificity
Spiral	**88.23%**	**94.02%**	66.66%
Meander	79.72%	**97.82%**	50%
Spiral + Meander	82.31%	96.19%	47.61%

Table 4. 5 :Results of Accuracy Sensitivity Specificity HandPD in CNN 3

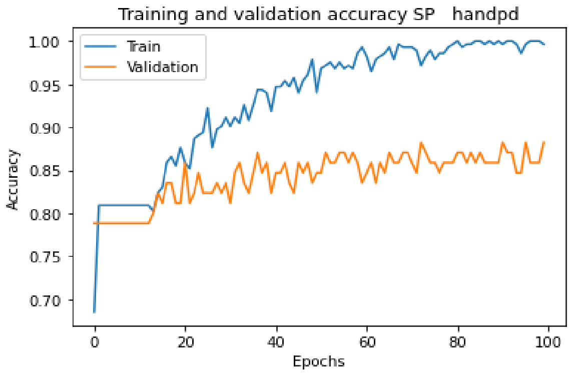


Figure 4. 16:Training and validation accuracy Spiral HandPD CNN3

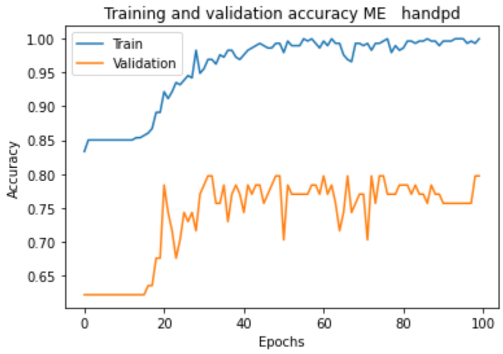


Figure 4. 17:Training and validation accuracy Meander HandPD CNN3

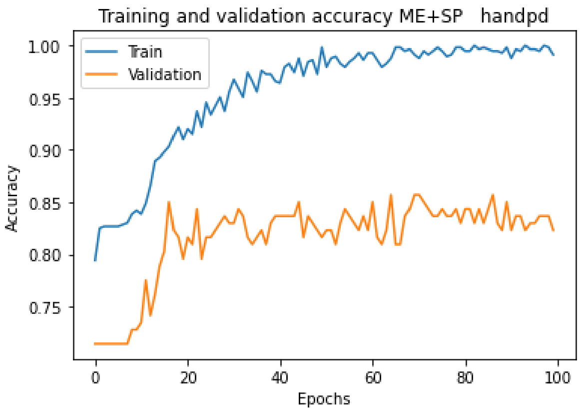


Figure 4. 18:Training and validation accuracy Spiral and Meander HandPD CNN4

2.3. NewhandPD

In the third application of the cnn3 model on the last "NewhandPD" data set, its results were very characteristic and balanced; the highest accuracy achieved in the spiral task was 96.29%, and the sensitivity was 96% in the meander task. In terms of privacy, it has achieved a perfect ratio. " 100%" in the "Spiral" and "circle" tasks, cnn3 had greater success in the " NewhandPD " dataset than cnn4 and cnn3 with the dataset "handPD, Drawing" As shown in the table **(Table 4.6).**

NewhandPD	Accuracy	Sensitivity	Specificity
Spiral	**96.29%**	92%	**100%**
Meander	94.44%	**96%**	93.10%
Circle	84.61%	66.66%	**100%**
Spiral + Meanders	89.71%	92%	87.71%
Spiral + Meander+ Circle	92.5%	92.85%	92.18%

Table 4. 6:Results of Accuracy Sensitivity Specificity NewhandPD in CNN3

Figure 4. 19:Training and validation accuracy Spiral NewHandPD CNN3

Figure 4. 20:Training and validation accuracy Meander NewHandPD CNN3

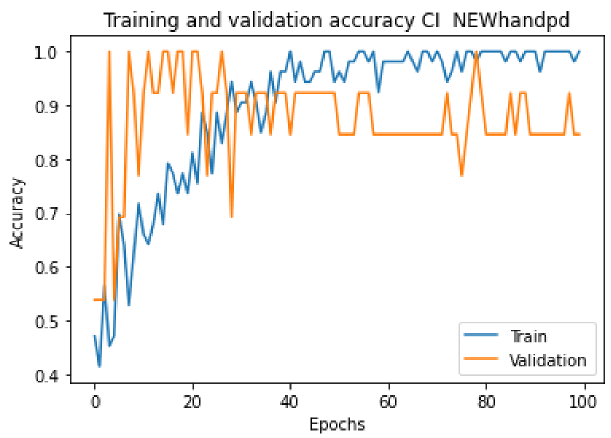


Figure 4. 21:Training and validation accuracy Circle NewHandPD CNN3

Figure 4. 22:Training and validation accuracy Spiral and Meander NewHandPD CNN3

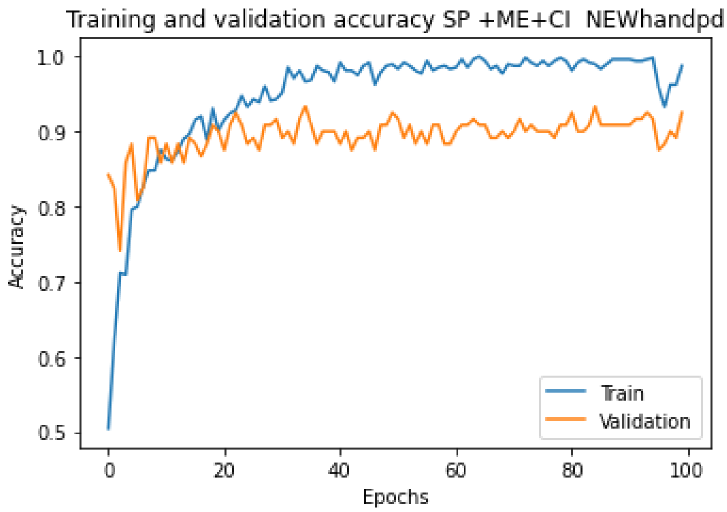


Figure 4. 23:Training and validation accuracy Spiral and Meander and Circle NewHandPD CNN3

3. The results of the four models

			VGG19	VGG16	CNN4	CNN3
DRAWING	SP	ACC	75%	80%	**90%**	70%
		SEN	55.56%	66.66%	**100%**	55.55%
		SPE	**90.90%**	90%	81.81%	81.81%
	WA	ACC	**100%**	**100%**	70%	70%
		SEN	**100%**	**100%**	70%	60%
		SPE	**100%**	**100%**	70%	80%
	SP+WA	ACC	87%	**90.24%**	73.17%	73.17%
		SEN	**85%**	**85%**	75%	60%
		SPE	90.47%	**95.23%**	71.41%	85.71%

HANDPD	SP	ACC	**92.94%**	91.76%	83.52%	88.23%
		SEN	**100%**	98.50%	92.53%	94.02%
		SPE	**66.66%**	**66.66%**	50%	**66.66%**
	ME	ACC	**83.78%**	**83.78%**	72.97%	79.72%
		SEN	97.82%	**100%**	95.65%	97.82%
		SPE	**60.71%**	57.14%	35.71%	50%
	SP+ME	ACC	**89.11%**	87.75%	82.99%	82.31%
		SEN	**99.04%**	**99.04%**	95.23%	96.19%
		SPE	**64.28%**	59.52%	52.38%	47.61%
NEWHAND	SP	ACC	94.44%	**100%**	88.88%	**96.29%**
		SEN	**100%**	**100%**	92%	92%
		SPE	89.65%	**100%**	86.20%	**100%**
	ME	ACC	92.59	**94.44%**	90.74%	**94.44%**
		SEN	88%	92%	92%	**96%**
		SPE	**96.55%**	**96.55%**	89.65%	93.10%
	CI	ACC	**92.30%**	92.23%	84.61%	84.61%
		SEN	**83.33%**	**83.33%**	**83.33%**	66.66%
		SPE	**100%**	**100%**	85.71%	**100%**

	ME+SP	ACC	94.39%	**97.19%**	90.65%	89.71%
		SEN	94%	**96%**	94%	92%
		SPE	94.73%	**98.24%**	87.71%	87.71%
	SP+ME+ CI	ACC	93.33%	**96.66%**	90%	92.50%
		SEN	92.85%	**94.64%**	83.92%	92.85%
		SPE	93.75%	**98.43%**	95.31%	92.18%

Table 4 .7 :Results of Accuracy Sensitivity Specificity in the four models (VGG16,VGG19.CNN4, CNN3)

4. Discussion of the reuslts

In Table (**Table 4.7**), we will analyze the results of testing the proposed models on three datasets (Drawing, HandPD, and Newhandpd).

First, in the spiral task, CNN4 performed better than the other models, with an accuracy of 90% and sensitivity of 100%. As for the specificity, it was 90.90%. As for the WAVE task, VGG16 and VGG19 had a significant role in accuracy, sensitivity, and specificity, with integrated ratios of 100% for each, and when combining spiral and wave, VGG16 achieved a good result. The accuracy is 90.24%, sensitivity is 85%, and specificity is 95.23%, and the best models applicable **for drawing** are CNN4, VGG16, and VGG19.

As for the HandPD dataset, the results you get in this cohort focus on VGG16 and VGG19. We find that VGG19 did well on the spiral task with 92.94% accuracy and 100% sensitivity and on the spiral +meander accuracy ratio. 89.11%, and its sensitivity is estimated at 99.04%. As for the meander task, VGG16 was good, with an accuracy of 89.78% and a sensitivity of 100%.

on the dataset NewhandPD

The results obtained centered on three models: cnn3, vgg16, and vgg19.

The "spiral" task, which has an accuracy of 96.29%, a sensitivity of 92%, and a specificity of 100%, is one of the notable advancements that cnn3 has made in comparison to prior datasets. Second, in the "meander" task, it scored 94.44 on accuracy, 96 on sensitivity, and 93.10 on specificity. Additionally, "meander + spiral" and "spiral + meander + circle" results are advanced.

In terms of VGG16 and VGG19, all of their performances were fantastic.

5. Comparison of results

In this table, we compare our results with those of [37] and [41] in the HndPD dataset in the task meander.

<table>
<tr><th colspan="2">MODEL</th><th>DATASEAT</th><th>ACCURACY</th></tr>
<tr><td colspan="2">VGG19</td><td rowspan="4">HandPD
‘meander’</td><td>83.78%</td></tr>
<tr><td colspan="2">VGG16</td><td>83.78%</td></tr>
<tr><td colspan="2">CNN4</td><td>72.97</td></tr>
<tr><td colspan="2">CNN3</td><td>79.72</td></tr>
<tr><td>L. ALI and all
[37]</td><td>Chi2 - Adaboost</td><td>HandPD
‘meander’</td><td>76.44%</td></tr>
<tr><td>C. R. Pereira [41]</td><td>SVM</td><td>HandPD
‘ meander’</td><td>66.72%</td></tr>
</table>

Table 4. 8: comparison results

We conclude from this table that the results achieved by VGG16, VGG19, and CNN3 were better than the two results of models chi2-Adaboost [37]and SVM [41] In a task meander in a HandPD dataset.

IV. Conclusion

At the end of this chapter, we can say that all models have good or acceptable results depending on the data set, so the accuracy in these models reached 100% in vgg16 and vgg19. As for CNN4, it achieved the highest accuracy of 90% in the drawing data set, and CNN3 witnessed a great development, and its accuracy reached 96.28% in the spiral task of the NewhandPD dataset. Finally, we conclude that transfer learning, as well as the CNN3, CNN4 models; can be applied to the detection of Parkinson's disease

General conclusion

Main objective of our thesis is to learn about Parkinson's disease through handwriting analysis using artificial intelligence and deep learning tools, especially convolutional neural networks, by working on it in Anaconda, and SpyderIDE platforms to write code. We also used Python to implement our system. In addition, we worked on three datasets in the form of images of Parkinson's disease. The Parkinson's drawing dataset contains 102 spiral and 102 wave samples. The second dataset is handpd, which contains 368 spiral chart images. The third and final dataset is newhandpd, which contains 594 images, including circles, drawings, and spirals. We have presented hypotheses for our thesis problem, "Handwriting analysis for Parkinson’s disease," of transfer learning with two variants of vgg16 and vgg19 to see if it produces an outcome or not in the field. For the second hypothesis, we only used the convolutional neural network (CNN3–CNN4) without adding any auxiliary models after applying these two hypotheses by following a set of work steps such as split data the pre-processing data set. We also worked on the scale for accuracy, sensitivity, and specificity. For vgg16, its results are so excellent that accuracy, sensitivity, and specificity all reach 100% individually in two datasets (dataset Dawing, NewhandPD).

For vgg19, its results were good, especially in the three datasets, from which we conclude that the first hypothesis was 100% successful. We say that transfer learning provides continuous results on a small dataset.

The second premise is to generate two CNN3/CNN4 models with the least number of layers without the help of any other model, thus achieving good results, especially CNN3, which had a major role in the NEWHANDPD data set with an accuracy of 96.29% in the spiral task. And CNN4 had a good result of 90.74% in the meander task.

The obtained hypothesis results prove that we can rely on the learning transfer (VGG16 and VGG19) in the handwriting analysis of Parkinson's disease, as in the CNN3 model, which contains 10 layers and is generally sufficient to give accurate results for Parkinson's and non-Parkinson's patients using handwriting. For CNN4, its results are good; it achieved the highest accuracy of 90% in the drawing dataset.

Finally, we can say that the proposed hypotheses can be well used in classifying the Parkinson's patient from the non-patient.

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