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Department of Electronics and Telecommunication

Thesis for Master Degree in
Automatic and Systems

Theme

Parkinson’s Disease Detection from Spiral and Wave Drawings using Convolutional Neural Networks

Submitted by

Brahim Khelifa & Dia Errahmane Boukhris

Board of examiners:

Mr. Chlaoua Rachid	MCB	President	UKM Ouargla
Mme. Bettayeb Nedjla	MCB	Examiner	UKM Ouargla
Mme. Charif Fella	Pr	Supervisor	UKM Ouargla
Mr. Benchabane Abderrazak	MCA	Co-Supervisor	UKM Ouargla

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Dedication

KHELIFA Brahim >>>

First, I would like to express my deep gratitude to **God** Almighty, who has given us strength, courage, and patience to carry out this task successfully. Implementation of this message would not have been possible without the contribution of many people, and I would like to express my deep gratitude to them.

I dedicate this work to my dear family, to my beloved parents who contributed to building my personality and pushed me towards achieving excellence. Thanks to my father who believed in my abilities and encouraged me to reach what I am now. For my mother, I thank you for your priceless love and giving and of course, all my friends, especially **Abdellaziz** and others that cheered for my success and seeked my well being

I cannot forget my colleague **'Boukhris diaerrahmane',** with whom I started this journey. Thank you for your continuous cooperation and encouragement. I also thank my teachers, led by **'Dr. Charif' fella'** and **''Benchabane abderrazak''**, who believed in our success and helped us achieve the best

BOUKHRIS Dia errahmane >>>

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I cannot forget my colleague **'Khelifa brahim'**, with whom I started this journey. Thank you for your continuous cooperation and encouragement. I also thank my teachers, led by '**Dr. Charif' fella'** and ''**Dr. Benchabane abderrazak''**, who believed in our success and helped us achieve the best.

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Finally, we would also like to thank anyone who participated directly or indirectly in the achievement of this work.

To all my colleagues and friends– Thank you so much.

Abstract:

Detecting parkinson's disease (PD) has become increasingly important in the medical field. Deep learning (DL), particularly Convolutional neural networks (CNNs), has shown great promise and has been extensively applied in various domains, including healthcare. this study introduces a detection system that leverages deep learning for a quick, accurate, and reliable PD diagnosis. Three pre-trained CNN models (ResNet50, DenseNet201, and AlexNet)are used for this system.

Keywords~ Deep Learning (DL), Parkinson’s disease (PD), Convolutional Neural Networks (CNNs), ResNet50, DenseNet201, AlexNet.

ملخص:

أصبح اكتشاف مرض باركنسون (PD) ذا أهمية متزايدة في المجال الطبي. أظهر التعلم العميق(DL)، ولا سيما الشبكات العصبية الالتفافية (CNNs)، نتائج واعدة وتم تطبيقه على نطاق واسع في مجالات مختلفة، بما في ذلك الرعاية الصحية. تقدم هذه الدراسة نظام اكتشاف يستفيد من التعلم العميق من أجل تشخيص PD سريع ودقيق وموثوق. تم استخدام ثلاثة نماذج CNN مدربة مسبقًا - ResNet50 DenseNet201 و AlexNet - لهذا النظام.

كلمات مفتاحية ~ مرض باركنسون, التعلم العميق، الشبكات العصبية الالتفافية (CNNs)،

AlexNet , ResNet50 ,DenseNet 201

Résumé :

La détection de la maladie de parkinson (MP) est devenue de plus en plus importante dans le domaine médical. L’apprentissage profond (AP), en particulier les réseaux de neurones convolutifs (CNN), s’est avéré très prometteur et a été largement appliqué dans divers domaines, y compris les soins de santé. Cette étude introduit un système de détection qui tire parti de l’apprentissage profond pour un diagnostic de MP rapide, précis et fiable. Trois modèles CNN pré-entraînés (ResNet50, DenseNet201 et AlexNet) sont utilisée pour ce système.

Mot-clé ~ Maladie de Parkinson (MP), apprentissage profond, neurones convolutifs (CNN) ResNet50, DenseNet201 et AlexNet

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Abbreviations

PD	: Parkinson's Disease.
DL	: Deep Learning.
CNN	: Convolutional Neural Networks.
AI	: Artificial Intelligence.
MI	: Machine Learning.
CAD	: Computer-Aided Diagnosis.
SVM	: Support Vector Machines.
ANN	: Artificial Neural Networks.
KNN	: K-Nearest Neighbors.
NN	: Neural Network.
BN	: Batch Normalisation.
ReLU	: Rectified Linear Unit.
FCL	: Fully Connected Layer.
DTL	: Deep Transfer Learning .
REM	: Rapid Eye Movement.
PD-MCI	: Parkinson's Disease Mild Cognitive Impairment.
PDD	: Parkinson's Disease Dementia.
SNpc	: Substantia Nigra pars compacta .
MRI	: Magnetic Resonance Imaging.
CART	: Classification And Regression Trees.
PCA	: Principal Component Analysis.
SNE	: Stochastic Neighbor Embedding.
DBNs	: Deep Belief Networks.
ST	: Spiral Template.
HT	: Handwritten Trace.
NB	: Naïve Bayes
OPF	: Optimum-Path Forest
PSD	: Power Spectral Density
RENN	: Recurrent Elman Neural Network
EMG	: Electromyography
BA,FA,RA	: Bat Algorithm, Firefly Algorithm, Random Algorithm

General Introduction

Artificial intelligence (AI) is a vital branch of computer science with countless research applications. AI aims to generate intelligent machines capable of processing information. machine learning (ML), the foundation of AI, is extensively used in various fields, especially disease diagnosis. both machine and deep learning technologies are crucial in computing, acting as experts for predictions and decision-making. deep learning, a subset of ML, focuses on acquiring data representations through increasing levels of abstraction. among various deep learning architectures, convolutional neural networks (CNNs) are prominent.[28]

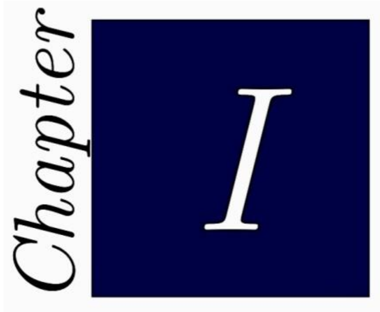
Parkinson’s disease (PD) is a progressive neurodegenerative disorder affecting millions worldwide, characterized by symptoms that worsen over time. Early detection is crucial for effective management and intervention. PD manifests through tremors (involuntary shaking, typically in hands or limbs at rest), bradykinesia (slowed movement complicating daily tasks), muscle rigidity (stiffness and tension restricting movement), and postural instability (compromised balance increasing fall risk). The underlying cause is the degeneration of dopamine-producing neurons in the brain's substantia nigra.[28]

We implemented a computer-aided diagnosis (CAD) system using CNN pretrained models such as AlexNet, ResNet50, and DenseNet201 on Spiral and Wave drawing images from the Kaggle database.

We divide our study into three chapters:

In the first, we will present generalities on deep learning, CNN, and some definitions of networks. In the second chapter will define the Parkinson disease and its symptoms and present its variants and who are the most at risk from it. and the methodology used for detection him (PD).

The third chapter will present a description of the performance evaluation metrics, the results of the tests performed with the pretrained models (Alexnet, ResNet50, and DenseNet201) based on Spiral and wave drawings images dataset.



Chapter I: An Overview on Deep learning

I.1. Introduction

Artificial intelligence (AI) is a field that combines computing with reliable datasets to facilitate problem solving. It aims to create machines capable of simulating certain capabilities of human intelligence. AI encompasses sub-domains such as machine learning (ML) and deep learning (DL), which are often used in conjunction with artificial intelligence, put simply, AI allows computers to think and act like humans.[29]

Machine learning is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions. It's like teaching a computer to learn from examples and make predictions or decisions based on patterns it discovers in the data. DL also represents learning methods from data where the computation is done through multi-layer neural networks and processing. The term "Deep" in the deep learning methodology refers to the concept of multiple levels or stages through which data is processed for building a data-driven model.[29]

One of the big differences between deep learning and ML in machine learning, the process of feature extraction is a crucial step. in ML algorithms, this step is carried out by human, which can be challenging and time-consuming, necessitating expertise in the field. however, in deep learning, feature extraction is automated by the algorithm itself.

The relationship between the three concepts AI, ML and DL is represented in the **Fig(I.1)**.

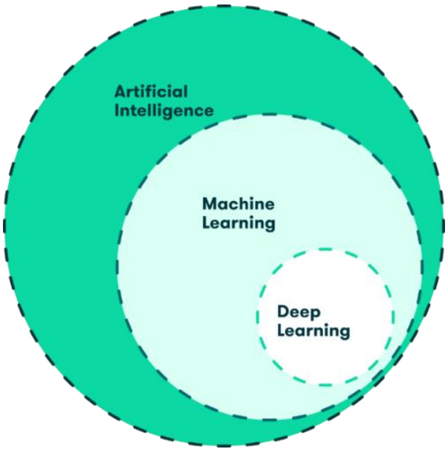


Fig (I.1): Relationship between the three concepts AI, ML and DL[29].

I.2. Machine learning

The objective of ML is to automatically generate knowledge from raw data (samples). This knowledge, also known as a model, can subsequently be utilized to make decisions. Based on the characteristics of the samples (whether they are labeled or not), there exist four categories of learning: supervised learning., unsupervised learning, semi-supervised learning, and reinforcement learning. [1] [2]

I.2.1. Types of learning

- **Supervised Learning**: In this approach, the algorithm learns from labeled data, where the input data is paired with the correct output. Examples include image classification and regression tasks. [4]
- **Unsupervised Learning:** Here, the algorithm learns from unlabeled data, finding patterns or structures within the data. Clustering and dimensionality reduction are common unsupervised learning tasks. [4]
- **Semi-Supervised Learning**: A combination of supervised and unsupervised learning, where the algorithm uses both labeled and unlabeled data. [3]
- **Reinforcement Learning**: The algorithm learns by interacting with an environment and receiving feedback (rewards or penalties) based on its actions. [3]

Machine learning (ML) algorithms, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Naive Bayes, Logistic Regression, and Decision Trees, have been widely used in various fields for classification and prediction tasks.

I.2.2. Neural network (NN)

A neural network (NN) is a computational model inspired by the complex functions of the human brain. It consists of interconnected nodes (artificial neurons) that process and learn from data, enabling tasks such as pattern recognition and decision making in machine learning, the supervised ML algorithm NN, which falls under the classification task, can be categorized into various types based on the network structure. [1]

1. **Architecture** :

1. An NN comprises layers of nodes (see **Fig I.2**):
    - **Input layer**: Receives external data.
    - **Hidden layers**: Process intermediate representations.
    - **Output layer**: Produces the final result.

- Each node connects to others, has its own associated weight, and a threshold.
- If a node's output exceeds the threshold, it activates and sends data to the next layer.

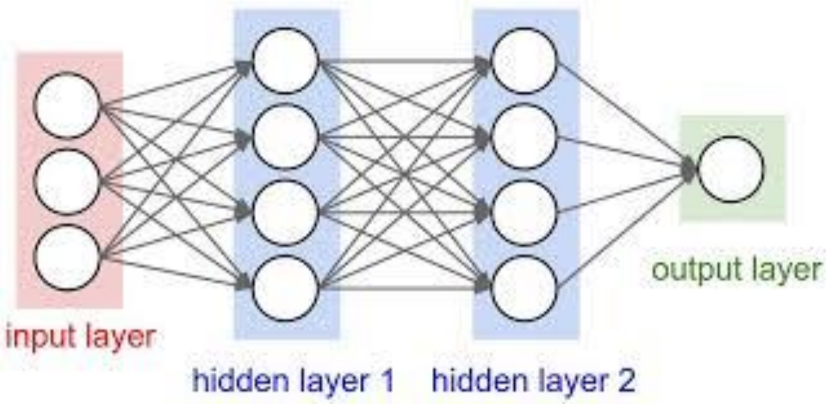


Fig (I.2): Example of the artificial neural network [1].

2. **Learning and Training :**
    - NNs rely on training data to learn and improve accuracy.
    - During training, they adjust their parameters (weights) to minimize the difference between predicted and actual target values.
    - Gradient-based methods like backpropagation estimate the parameters.
3. **Activation Function :**
    - Each node computes its output using an activation function.

- Common activation functions include sigmoid, ReLU, and tanh (see **Fig I.3**)

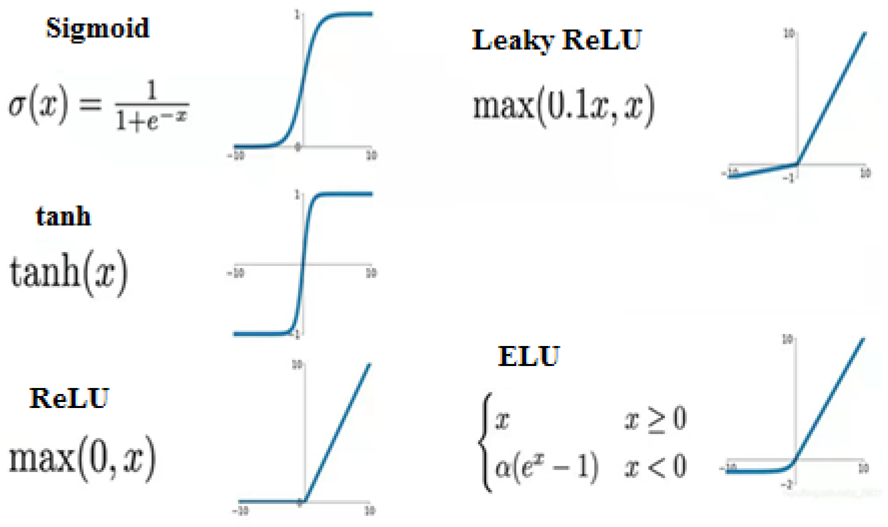


Fig (I.3): Somme Non-linear activation function [30]

I.3. Deep Learning

Deep learning (DL), a branch of machine learning (ML) and artificial intelligence (AI). DL technology, which stems from artificial neural networks (ANN) and learns from data, has emerged as a popular subject in the field of computing. It is extensively utilized in diverse fields such as healthcare, visual recognition, text analytics, and more. Nevertheless, constructing a suitable DL model poses a significant challenge due to the ever-changing nature and complexities of real-world problems and data. [5] [6]

I.3.1. Convolutional neural network (CNN)

A convolutional neural network (CNN), also known as a convnet, is a specialized type of deep learning neural network designed for tasks involving image and video analysis, a Convolutional Neural Network (CNN) is derived from the human visual cortex and is capable of handling large volumes of data, enhancing its learning capabilities. Additionally, CNN utilizes convolutional operations in its layers, typically including at least one layer. This specialization enables the network to effectively process data with grid-like structures, such as image data. the layers commonly found in a CNN: input layer, convolutional layers, activation layer, pooling (Subsampling) layer, and fully connected layer (see **Fig I.4**).[5][6]

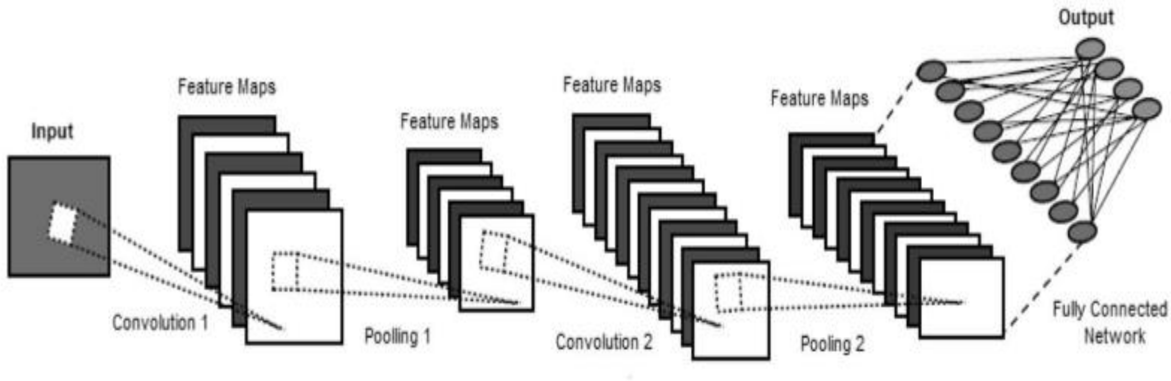


Fig (I.4): CNN Architecture example [5][6]

Some literature considers convolution and nonlinear activation to form the convolution layer, with pooling (sub-sampling) as the second layer. Occasionally, batch normalization (BN) layers are incorporated to enhance the performance of a CNN. These layers are typically added before the non-linear activation layer.

1. **Convolutional Layers:** A convolution layer is a fundamental component in convolutional neural networks (CNNs), used for processing input data through the application of the convolution operation. It contains a set of convolutional kernels (also called Filters), which gets convolved with the input image to generate an output feature map.[5][6]

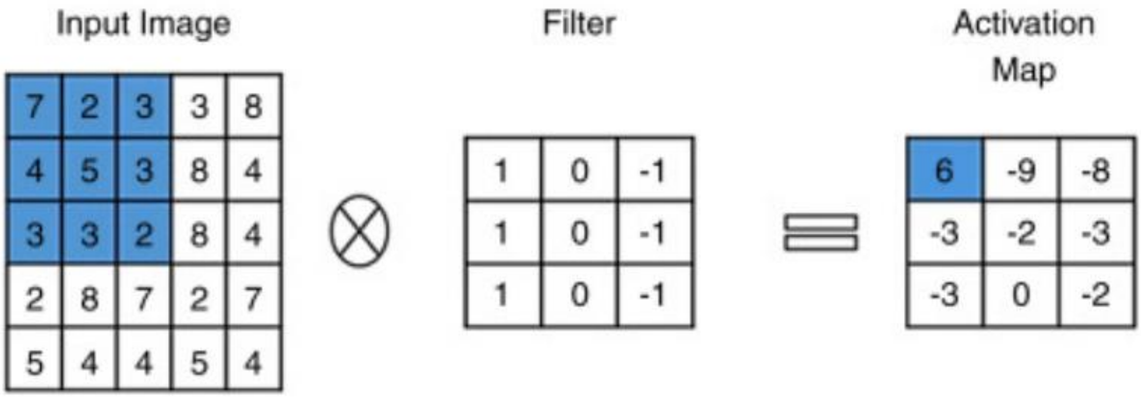


Fig (I.5): A graphical example of the convolution process.[5,6]

2. Activation layer: In neural networks, activation functions play a crucial role in introducing nonlinearity to the model. Without these nonlinearity transformations, neural networks would essentially behave like linear regression models, limiting their ability to learn complex relationships from data. Common nonlinear activation functions: Rectified Linear Unit (ReLU), Sigmoid, and Leaky RELU.[5][6]

3. **Pooling (sub-sampling) layer:** A pooling layer is usually incorporated between two successive convolutional layers. The pooling layer reduces the number of parameters and

computation by down-sampling the representation. There are different types of pooling techniques are used in deferent pooling layers such as max pooling, min pooling, average pooling, gated pooling, tree pooling, etc. Max Pooling is the most popular and mostly used pooling technique. Additionally, pooling layers help control overfitting by summarizing important features.

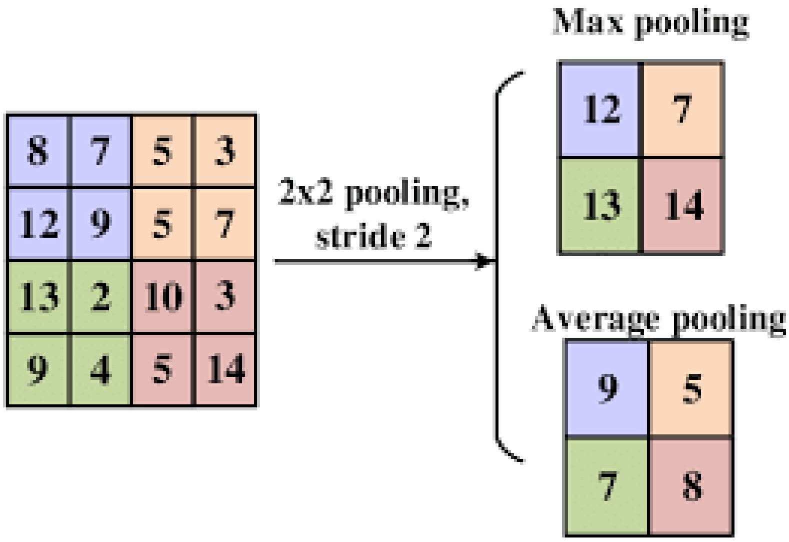


Fig (I.6): Examples for max and average pooling layer.[5][6]

4. **Fully connected layer:** In CNNs, FC layers often come after the convolutional and pooling layers. They are used to flatten the 2D spatial structure of the data into a 1D vector and process this data for tasks like classification. The combination of Flatten Layer with Fully Connected Layer and SoftMax Layer comes under Classification section of Deep Neural Network.

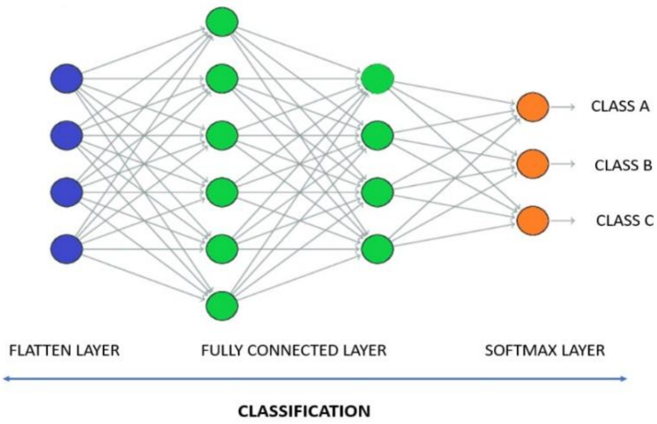


Fig (I.7): Fully connected layer [5][6]

The convolutional and pooling layers work together to extract features from the input image, while the fully connected layers and the output layer are responsible for classifying these features into final class labels. The class with the highest probability in the output layer is considered the final prediction for the input image.

I.3.2. Training a Convolutional Neural Network (CNN)

Training deep neural networks, including Convolutional Neural Networks (CNNs), remains a challenging and active area of research. In CNNs, the training process involves learning the weights of the layers to achieve optimal performance, such as accurate classification.

CNNs typically consist of several layers, with the first layer being the convolutional layer, acting as a feature extractor, and subsequent layers acting as classifiers. During training, there are two sets of weights to consider: the convolutional layer weights and the classification weights.

The process of adjusting the value of the weights is defined as the “training” of the neural network. Initially, the CNN starts with random weights. During training, the neural network is fed a large dataset of images labeled with their corresponding class labels. With each epoch, the neural network becomes increasingly accurate at classifying and correctly predicting the classes of the training images. After training, we use a separate test dataset to evaluate the model's accuracy. The test dataset consists of labeled images that were not included in the training process. Each test image is fed to the CNN, and the output is compared to the actual class label. This evaluation assesses the CNN's prediction performance. If a CNN shows high accuracy on the training data but performs poorly on the test data, it is said to be “overfitting.” Overfitting often occurs when the training dataset is too small.[7]

I.4. Deep Transfer Learning (DTL)

Transfer learning is a technique that leverages previously learned knowledge from a pre-trained model to solve a new task with minimal training or fine-tuning. Figure I.8 illustrates the general structure of the transfer learning process, where knowledge from the pre-trained model is transferred into a new deep learning model. [8]

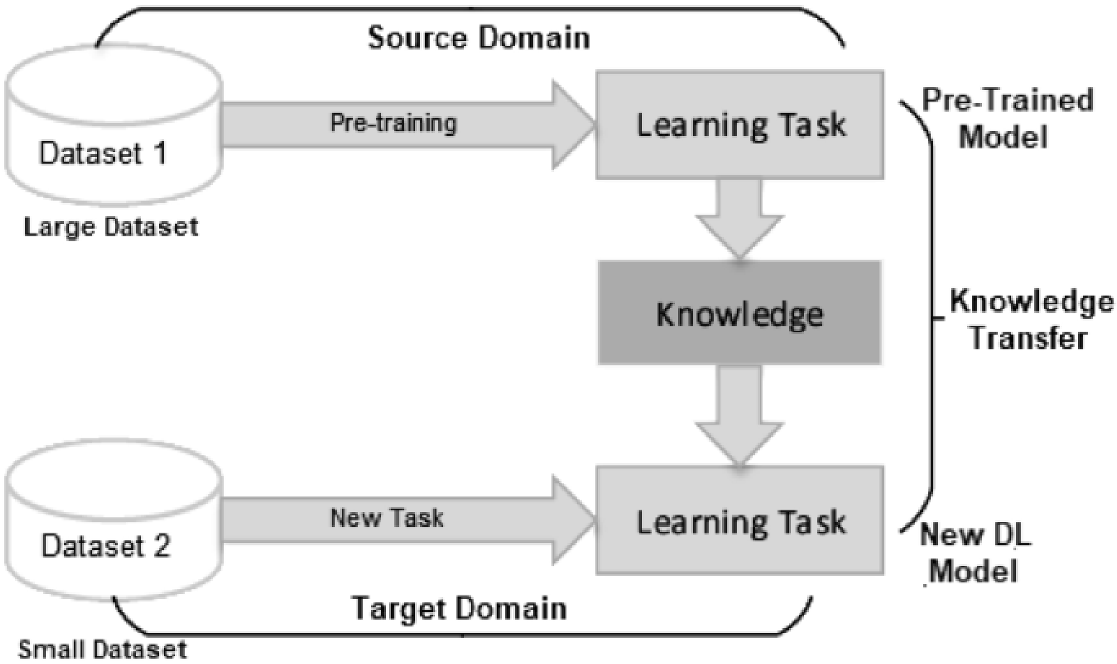


Fig (I.8): A general structure of transfer learning process, where knowledge from pre-trained model is transferred into new DL model [8]

Transfer learning leverages the knowledge gained from a pre-trained model to effectively address new tasks with minimal additional training. This two-stage approach, involving pre-training and fine-tuning, has proven to be highly effective across various fields, leading to the development of numerous deep transfer learning methods that enhance efficiency, performance, and speed in training deep neural networks.[8]

I.5. Most Popular Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have become the backbone of many computers vision tasks due to their ability to automatically and adaptively learn spatial hierarchies of features from input images. Over the years, several CNN architectures have stood out for their performance and innovation. Here are some of the most popular CNN architectures:

I.5.1. AlexNet

AlexNet, developed by Alex Krizhevsky, was created for the ImageNet LSFRC-2010 competition and secured first place. It features eight weight layers: five convolutional layers and three fully connected layers, with max-pooling layers following the first, second, and fifth convolutional layers. The first convolutional layer uses 96 filters of size 11 × 11, a stride of 4 pixels, and 2 pixels of padding. The stride and padding for the other convolutional layers are set to 1 pixel. The second convolutional layer has 256 filters of size 5 × 5, while the third, fourth, and fifth convolutional layers have 384, 384, and 256 filters, respectively, all with a size of 3 × 3. [11] [25]

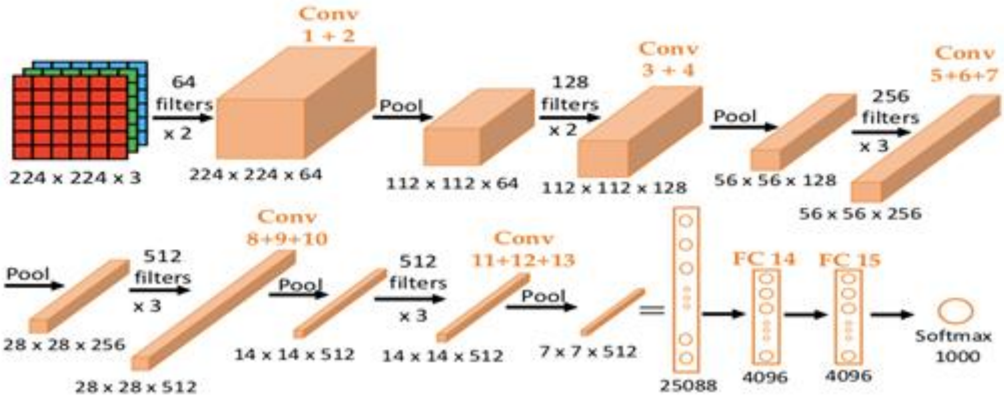


Fig (I.9): AlexNet CNN architecture [25]

I.5.2. ResNet 50

ResNet, developed by Kaiming He from Microsoft, introduced the "identity skip connection" to address the vanishing gradient problem. This innovation led to the creation of the ResNet model, which won the ILSVRC 2015 challenge with a significant performance improvement, reducing the top-5 error rate to 3.6%, surpassing human-level performance on the same dataset. This achievement set new standards in classification, detection, and localization tasks. Despite being 8 times deeper than VGGNets (22 layers) with its 152 layers, ResNet has lower complexity than VGGNets (16/19). The ResNet-50 architecture is organized into a series of stages, each composed of a combination of convolutional layers, batch normalization, activation functions (ReLU), and pooling layers, followed by fully connected layers at the end. [8][9]

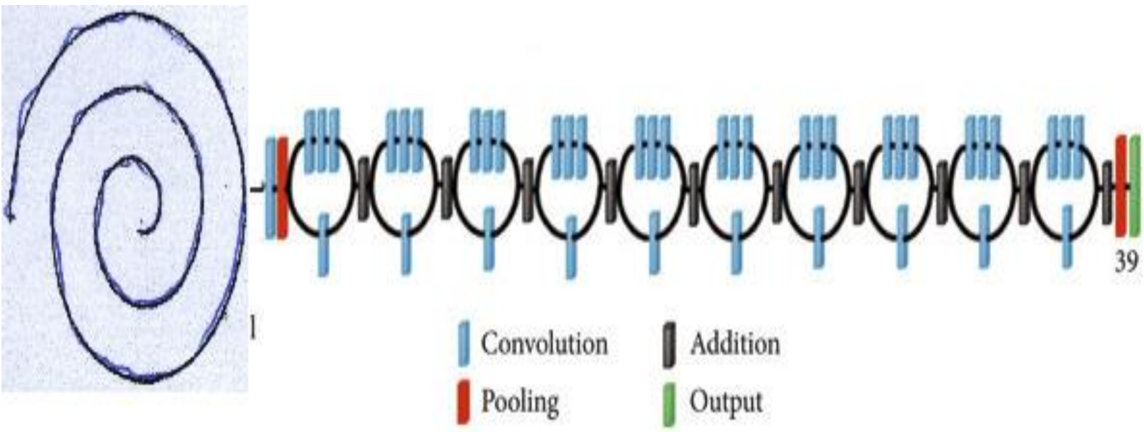


Fig (I.10): ResNet50 CNN architecture[8][9]

I.5.3. DenseNet 201

In 2016, Huang introduced DenseNet, which emerged as the champion of ILSVRC-2016. The concept behind DenseNet involves utilizing residual mapping to transmit the output of each block to all subsequent blocks within each dense block of the network. By propagating information in both forward and backward directions during model training, DenseNet enhances feature propagation capabilities and addresses the issue of vanishing gradients. DenseNet201 is a variant of the Dense Convolutional Network (DenseNet) architecture specifically designed for image classification. DenseNet, introduced "Densely Connected Convolutional Networks," features dense connections between layers. The "201" in DenseNet201 indicates that this model consists of 201 layers.[8]

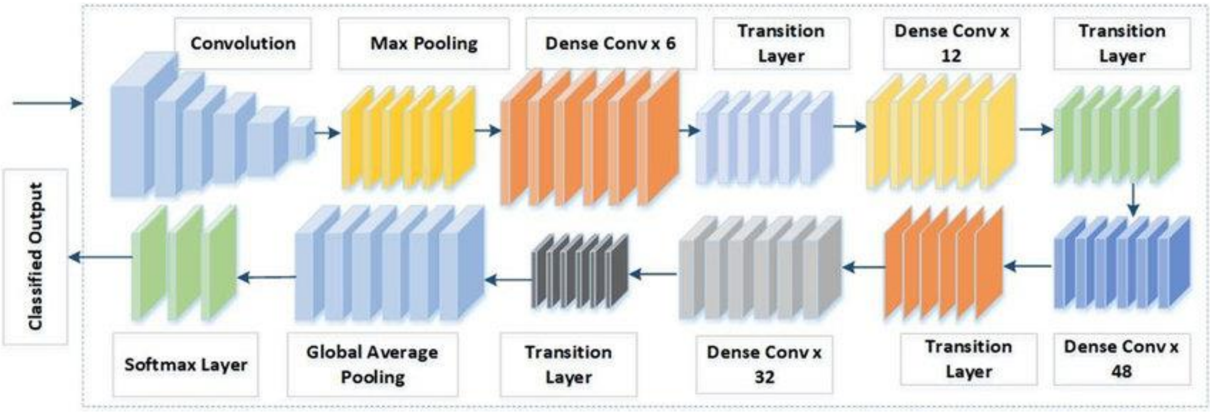


Fig (I.11): DenseNet201 CNN architecture[8]

I.5.4. VGG 19

VGG19 is a deep convolutional neural network with 19 layers, designed for image classification. It was pretrained on the ImageNet dataset, which includes over a million images and 1000 object categories. As illustrated in Figure 6, VGG19 comprises 5 convolutional blocks, each containing multiple sub-layers, totaling 16 convolutional layers, along with 4 max-pooling layers. The fully connected layers (FC1, FC2) and the SoftMax layer are responsible for storing and classifying the extracted image features.[10]

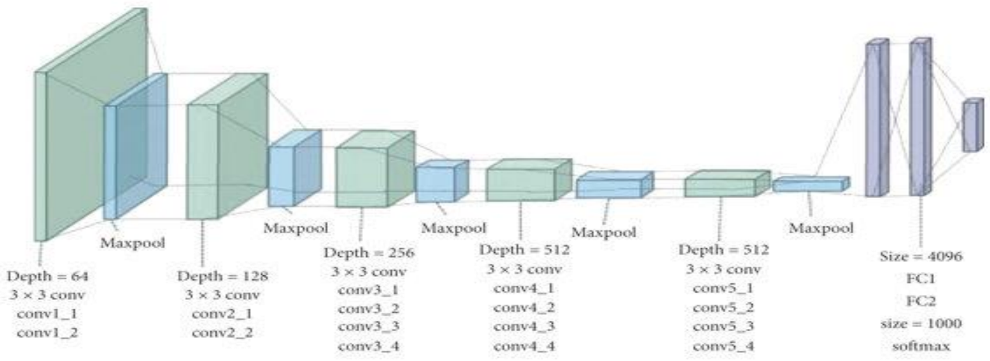


Fig (I.12): VGG 19 CNN architecture[10]

I.6. Multimodal Classification

Multimodal classification refers to the process of classifying data that involves multiple modalities or types of information. These modalities can include text, images, audio, video.The goal of multimodal classification is to leverage the complementary information provided by different modalities to improve the overall classification performance. One of the key challenges in multimodal classification is how to effectively fuse information from different modalities. This fusion can happen at different levels, including data-level fusion, feature-level fusion, and decision-level fusion (see Fig I.13) .

I.6.1. Data Level Fusion

At the data level, the raw data from different modalities are combined into a single representation before any further processing. For example, ccombining data from different imaging modalities (MRI, CT, PET) for improved diagnosis.

I.6.2. Feature Level Fusion

Feature-level fusion involves extracting features from each modality separately and then combining these features into a single feature vector. This could involve techniques like concatenation, where the features are simply appended together.

I.6.3. Decision Level Fusion

Decision-level fusion occurs after each modality has independently made a classification decision. These decisions are then combined to make a final decision. This could involve techniques like majority voting, where the class with the most votes from the individual modalities is chosen.

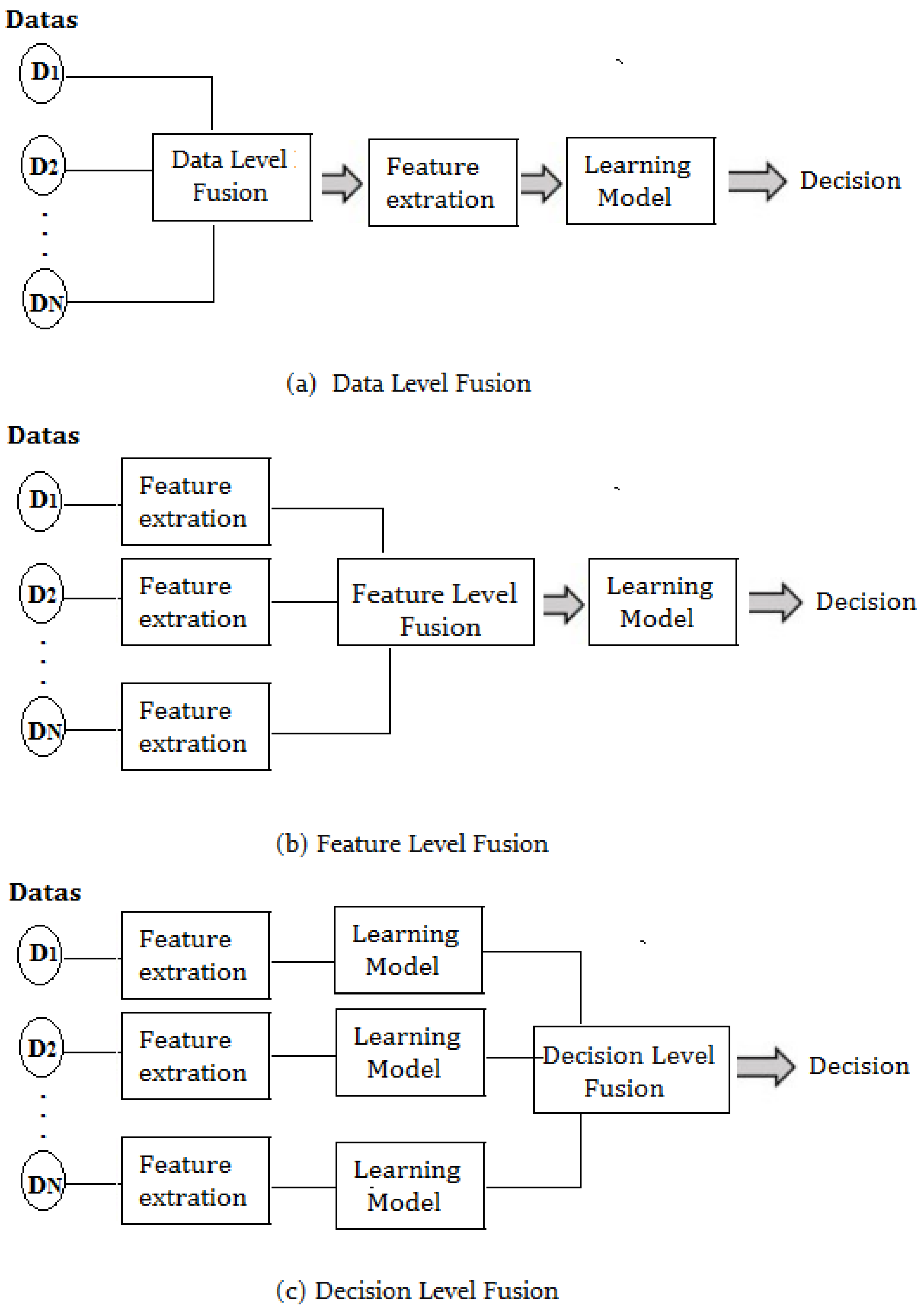


Fig (I.13): Three levels for multimodal fusion: (a) Data Level Fusion;(b) Feature Level Fusion; (c) Decision Level Fusion [27]

Each fusion level has its advantages and challenges. Data-level fusion can be computationally expensive but may capture more complex relationships between modalities. Feature-level fusion requires careful feature extraction and alignment but can be more interpretable. Decision-level fusion is simpler but may not fully exploit the complementary information in the modalities. The choice of fusion level depends on the specific characteristics of the dataset and the classification task.

I.7. Evaluation Metrics for Classification Task

Model evaluation is the process that uses some metrics which help us to analyze the performance of the model. Model evaluation is a critical process in machine learning and deep learning that involves assessing the performance of a trained model using various metrics. These metrics help determine how well the model is performing on tasks such as classification or regression.

I.7.1. Confusion Matrix

A confusion matrix is a structured representation showing the counts of true positives, true negatives, false positives, and false negatives. It organizes instances based on their actual class (rows) and their predicted class (columns). Within this matrix, four key quantities are tracked: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

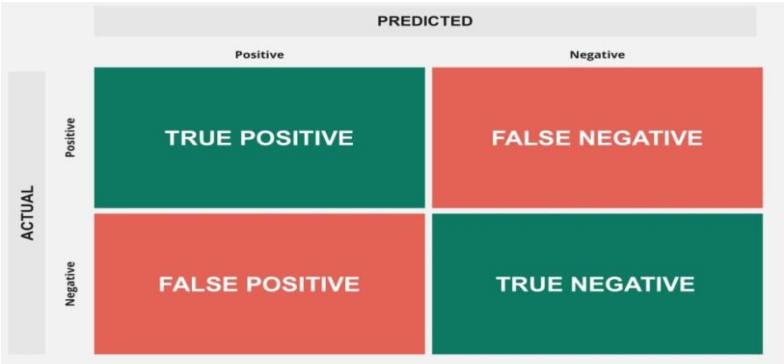


Fig (I.14): Confusion Matrix [26]

- **True positive (TP)** represents the quantity of instances correctly identified as belonging to the target class.
- **True negative (TN)** signifies the count of instances accurately recognized as not belonging to the target class.
- **False positive (FP)** indicates the number of instances incorrectly labeled as belonging to the target class when they do not.

- **False negative (FN)** denotes the quantity of instances erroneously classified as not belonging to the target class when they do.

Now we can analyse the confusion matrix by calculating several metrics including:

Specificity (SP) or true negative rate (TNR):

$$SP = TN / (TN + FP) \tag{I.1}$$

Sensitivity (SE) or true positive rate (TPR) sometimes called recall:

$$SE = TP/(TP + FN) \tag{I.2}$$

Precision (P):

$$P = TP/(TP + FP) \tag{I.3}$$

Classification accuracy (CA):

$$CA = (TP + TN)/(TP + FN + TN + FP) \tag{I.4}$$

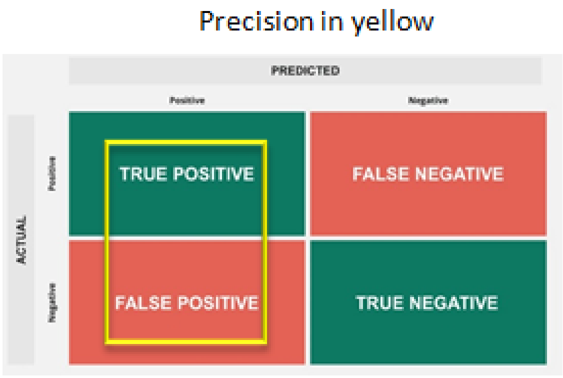


Fig (I.15): Precision [26]

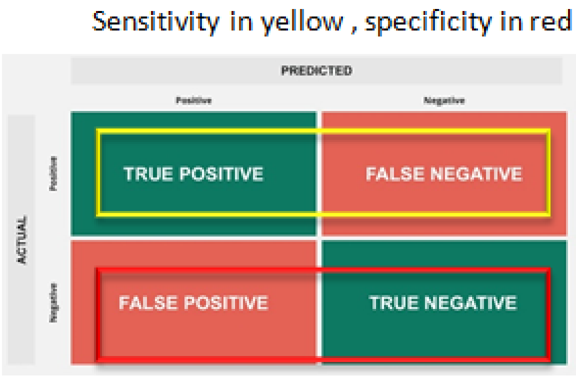


Fig (I.16): Sensitivity and Specificity [26]

I.7.2. Training time

This metric represents the duration, in minutes, taken by the model to complete the training process. We computed this metric individually for each fold within every experiment.

I.7.3. Plot training accuracy & error VS epoch

Initially, it's essential to understand that one epoch corresponds to a single pass of the dataset through the neural network, involving both forward and backward propagation. The depicted plot provides insights into the evolution of model performance, specifically focusing on training accuracy and error across epochs. Typically, as training progresses, classification accuracy tends to rise while error diminishes, indicating the model's learning process.

I.7.4. Plot validation accuracy & error VS epoch

This plot shares similarities with the previous one, but here we depict the classification accuracy and error during the validation process rather than during training. In essence, it offers insights into how the model performs on unseen data, as opposed to the training data. Similar to the previous plot, we observe trends in classification accuracy and error across epochs, providing valuable information about the model's generalization capability.

I.8. Conclusion

In this chapter, we have provided a comprehensive overview of deep learning, a powerful subset of machine learning that employs multi-layered neural networks to model complex patterns in data. We explored key concepts such as neural networks, Convolutional Neural Networks (CNNs), and transfer learning. CNNs, with their ability to process and analyze image data effectively, are particularly useful for medical imaging tasks. Transfer learning has emerged as a powerful strategy that leverages pre-trained models to significantly reduce the need for large, labeled datasets while enhancing model performance. In this work, we will use transfer learning techniques in PD detection and early diagnosis, improving patient outcomes by enabling timely intervention.

Chapter II

Chapter II: An Overview on Parkinson's disease detection

II.1. Introduction

Parkinson's disease (PD) is a condition that occurs when cells malfunction or sustain damage in a specific part of the brain known as the substantia nigra pars compacta. These cells play a crucial role in producing dopamine, a vital chemical substance. Over time, these cells are lost, leading to a deficiency of dopamine in the brain. This dopamine deficiency affects various motor behaviors in the body, including walking, writing, and even smiling.

Parkinson's disease develops gradually, often beginning with a barely noticeable tremor in just one hand. However, while tremors are the most well-known sign of Parkinson's disease, the disorder also commonly leads to a slowing or freezing of movement. Friends and family may observe that your facial expressions become limited or absent, and your arms do not swing when you walk. Speech often becomes soft and mumbled. As Parkinson's progresses, symptoms tend to worsen. Although there is no cure for Parkinson's disease, various medications can help manage its symptoms.

In general, as reported, parkinson's disease is characterized as a chronic, progressive neurodegenerative disorder. It affects individuals worldwide, particularly in countries with a high average age of the population. According to the parkinson's disease foundation (2015), approximately 10 million people globally suffer from PD, with one million of them residing in the United States. The Parkinson's Disease Society website states that one in every 500

British individuals is affected by this disease, and this number is expected to triple in the next 50 years. Typically, PD worsens over time and predominantly impacts people aged 50 to 70. Although James Parkinson, a British physician, first described PD in 1817, there is still no definitive cure for the condition. [12]

II.2. PD Types and Symptoms

The symptoms of Parkinson's disease can vary from person to person. Early signs may be subtle and can go unnoticed for months or even years. Typically, symptoms begin on one side of the body and tend to be more pronounced on that side. Common signes and symptômes of Parkinson's include [13] :

- **Tremor**, a characteristic shaking associated with Parkinson's disease, frequently starts in one hand. A common movement is the back-and-forth rubbing of the thumb and forefinger, known as pill-rolling. However, it's important to note that not all individuals with Parkinson's disease experience significant tremors.

- **Slowed motion (bradykinesia)** is a common symptom of Parkinson's disease. As the condition progresses, it can significantly impair your ability to initiate voluntary movements. Simple tasks may become challenging and time-consuming. When walking, your steps may become shorter and shuffling. In some cases, your feet may even freeze to the floor, making it difficult to take that initial step.

- **Rigid Muscles**: Muscle stiffness often occurs in the limbs and neck. In some cases, the stiffness can be severe, limiting the range of movement and causing pain.
- **Impaired Posture and Balance**: Parkinson's disease can lead to stooped posture. Imbalance is also common, although it is usually mild until the later stages of the disease.
- **Loss of Automatic Movements**: Unconscious acts such as blinking, smiling, and swinging your arms while walking is normal for humans. However, in Parkinson's disease, these movements tend to diminish or even disappear. Some individuals may develop a fixed staring expression with unblinking eyes, while others may no longer gesture or appear animated when they speak.
- **Speech Changes**: Many people with Parkinson's disease experience speech difficulties. You may speak more softly, rapidly, or in a monotone. Slurring or repeating words and hesitating before speaking are also common [13].

Some of the non-motor symptoms of Parkinson's disease (PD), such as hyposmia, rapid eye movement (REM), sleep behavior disorder, constipation, and depression, may emerge before any motor symptoms by several years. Many patients also experience cognitive dysfunction, which ranges from mild cognitive impairment (PD-MCI) to PD dementia (PDD)[13] .

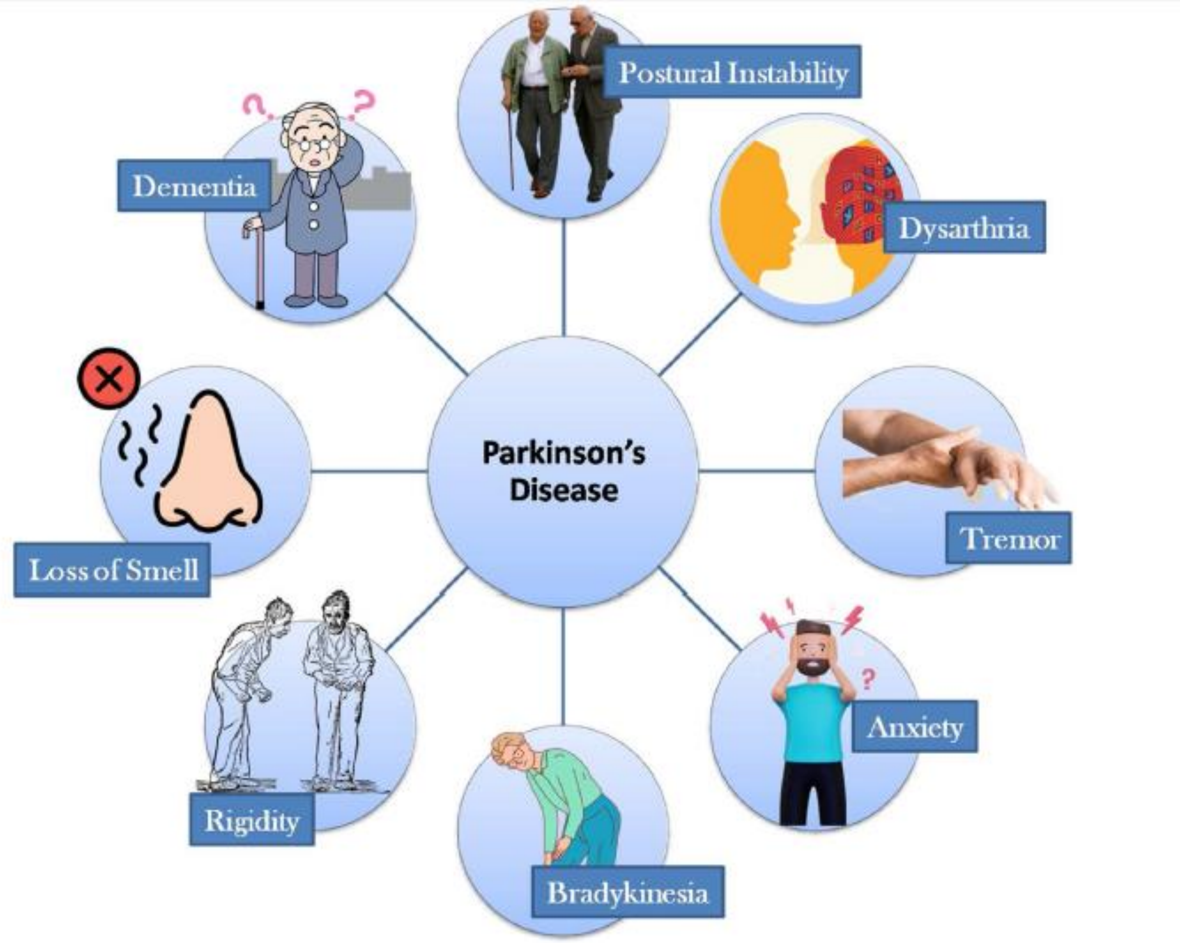


Fig (II.1): Some signs and symptoms of Parkinson's disease.[13]

In several cases, PD-MCI emerges in the early stages of the disease, while PDD tends to occur after approximately 20 years of having PD. PD-MCI is characterized by thinking and memory problems that deviate from what is expected with normal aging but do not prevent the patient from carrying out daily routine activities. Diagnosing PD-MCI is crucial because it could be a transition to PDD. Include:

- Impaired short-term memory.
- Executive dysfunction.
- Attention impairment.

- Visual-spatial deficit.
- Behavioral or neuropsychiatric symptoms, such as psychotic symptoms (hallucinations), changes in personality and mood, anxiety, and apathy.

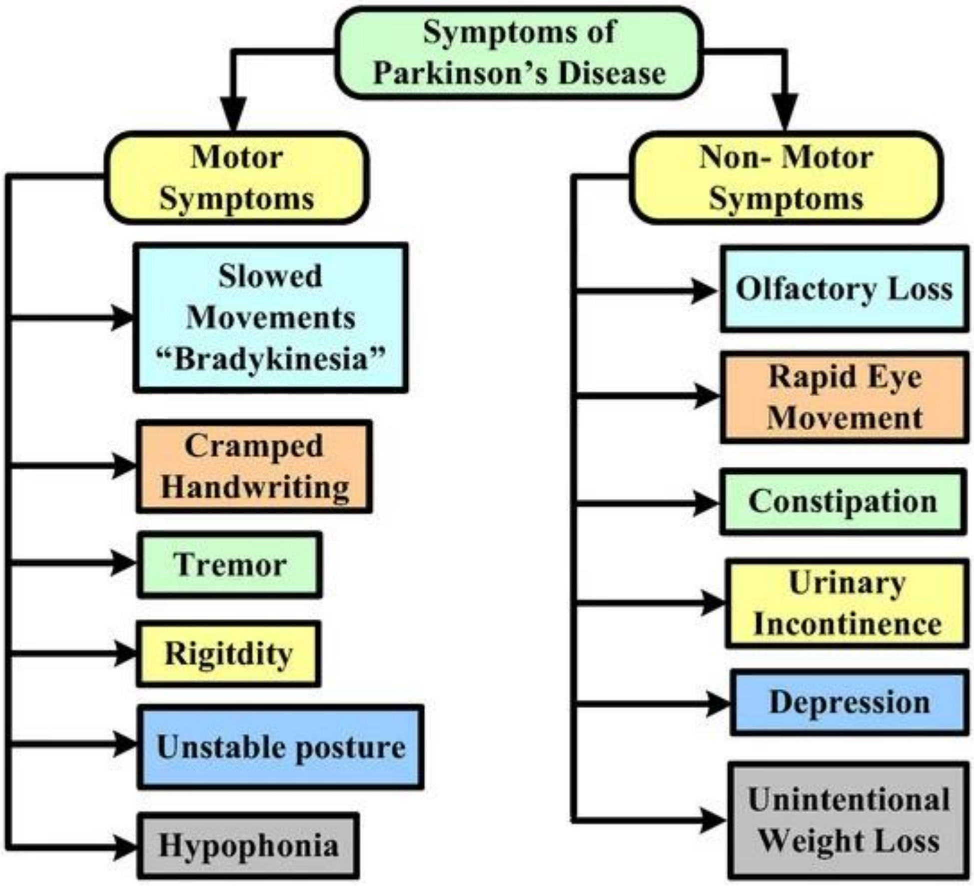


Fig (II.2): Symptoms of Parkinson's disease.[13]

II.3. Clinical View

Parkinson's disease (PD) typically presents unilaterally and insidiously. The disease follows a relentless progressive course, with motor symptoms gradually increasing. Additionally, a range of non-motor symptoms emerges, leading to functional impairment and disability. These non-motor symptoms include autonomic dysfunction, pain, skin issues, sleep disturbances, and neuropsychiatric symptoms. Patients with PD often experience significant functional limitations, a diminished health-related quality of life (HRQOL), and increased mortality compared to the general population.[14]

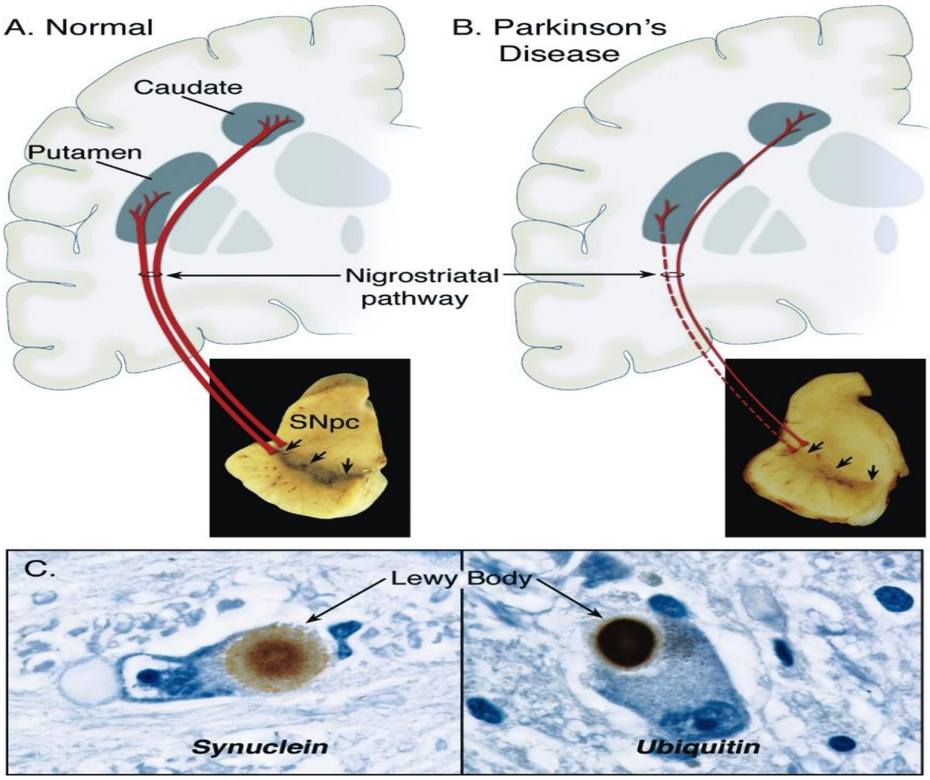


Fig (II.3): Neuropathology of Parkinson's Disease [14]

II.4. Parkinson's disease diagnosis

Diagnosing parkinsonian disorders continues to be a major clinical challenge, with Parkinson's disease (PD) having error rates as high as 24%. The growing elderly population emphasizes the importance of accurately and promptly diagnosing these syndromes to enable timely intervention. [15]

II.4.1. Diagnosis by MRI (Magnetic Resonance Imaging)

Parkinsonism, characterized by resting tremor, rigidity, bradykinesia, and postural instability, includes both Parkinson's disease (PD) and atypical Parkinsonism. However, distinguishing between these conditions can be challenging, especially in the early stages, due to overlapping symptoms. This is where multimodal MRI steps in. Multimodal MRI enhances our understanding of the pathophysiology of Parkinsonian disorders. It provides structural and quantitative MRI sequences that serve as sensitive biomarkers for different tissue properties. These sequences detect abnormalities specific to each disease, aiding in accurate diagnosis.[16]

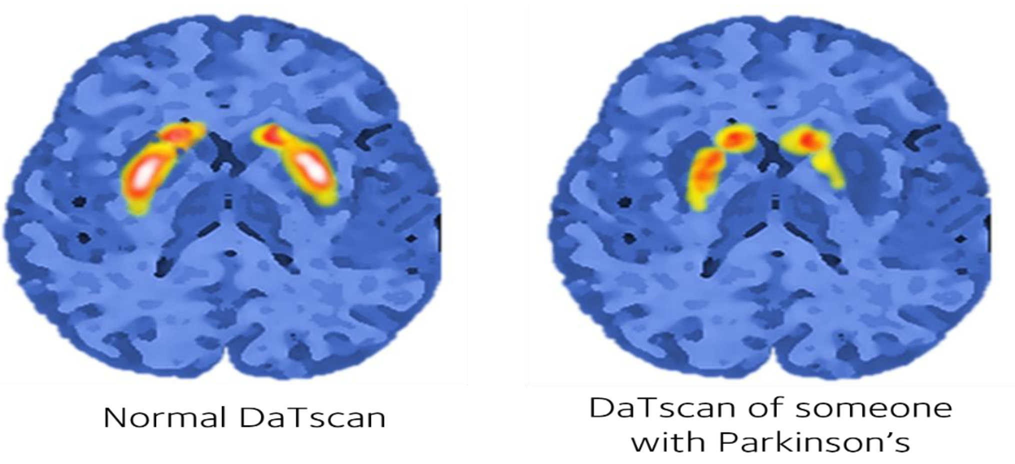


Fig (II.4): MRI used to identify Parkinson's disease biomarkers [16]

II.4.2. Diagnosis by hands and drawing

Interlocking finger test: The interlocking finger test is a physical assessment that involves tangling the fingers of the hands to assess flexibility and joint movement. The person extends his arms, confronts each other's palms, bows his fingers, tries to line the finger nets with a particular position.[17]

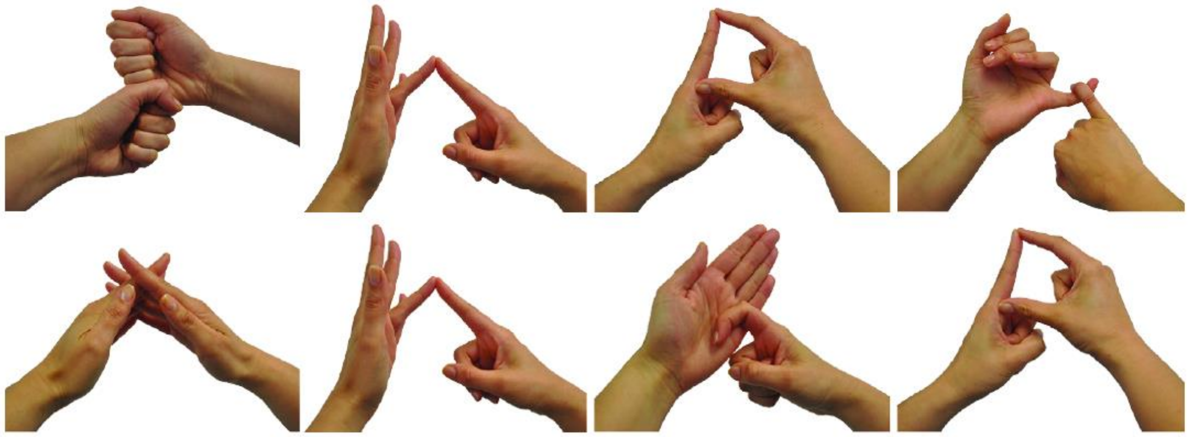


Fig (II.5): Interlocking finger test [17]

Handwriting test: The examination of patients' handwriting has become an important auxiliary method for the diagnosis and treatment of Parkinson's disease which can be used for early self-diagnosis of patients with Parkinson's disease.[18]

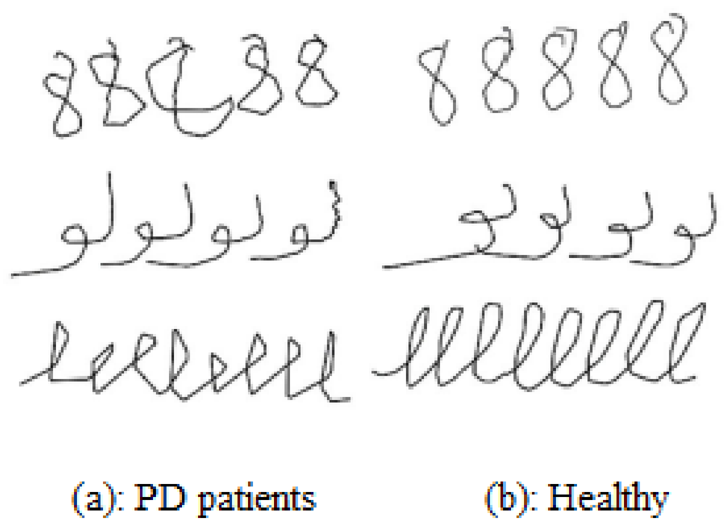


Fig (II.6): Example of Handwriting test [18]

Spiral and wave drawing Test: This test involves drawing a spiral and wave shape on a sheet of paper. The Researchers have found that analyzing writing speed and pen pressure during this task can help detect early signs of Parkinson’s disease. The spiral and wave drawing test is a simple yet effective way to assess fine motor control and coordination.[19]

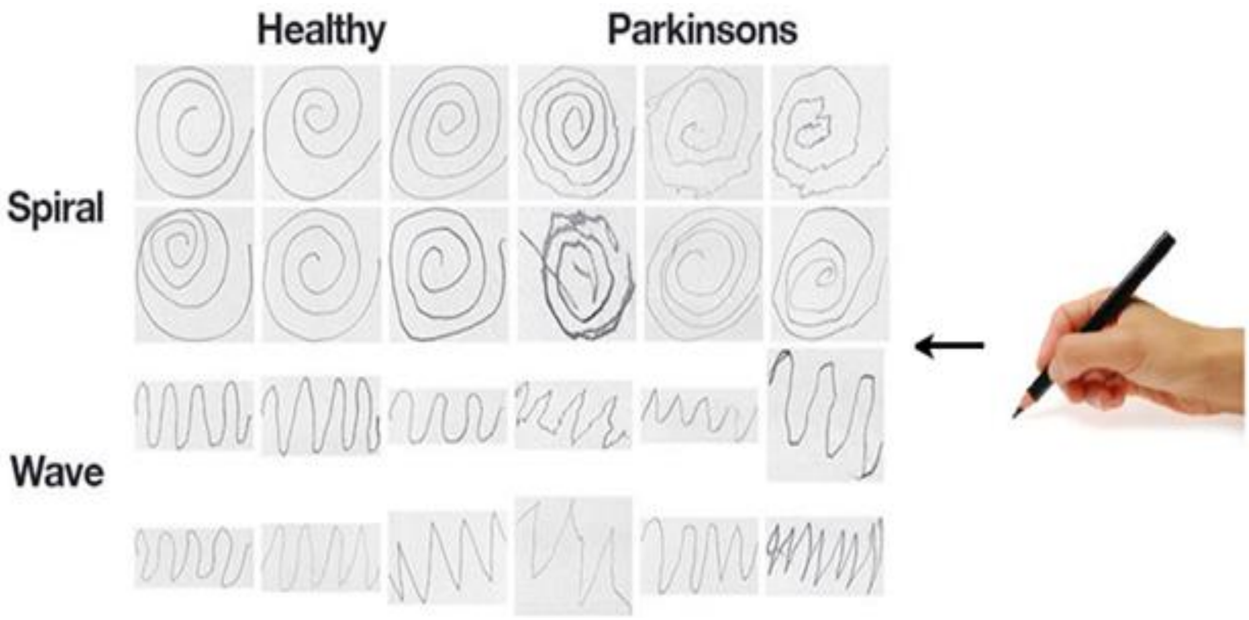


Fig (II.7): Spiral and wave drawing test [19]

Many studies have been proposed that use handwriting for detecting and monitoring PD, since abnormal handwriting is a well-recognized manifestation of PD. Handwriting anomalies may appear years before at the early stages of the disease and thus may be one of the first signs of PD.

II.4.3. Speech Test

Speech disorders are particularly prevalent in Parkinson's disease. The speak is softly or quickly or hesitate before talking. The speech may be more of a monotone rather than have the usual speech patterns. The healthy speech is regular while the speech from the Parkinson's sufferer is very irregular with high values of jitter, shimmer, and a low harmonic-to-noise ratio. (See Fig II .8).[20]

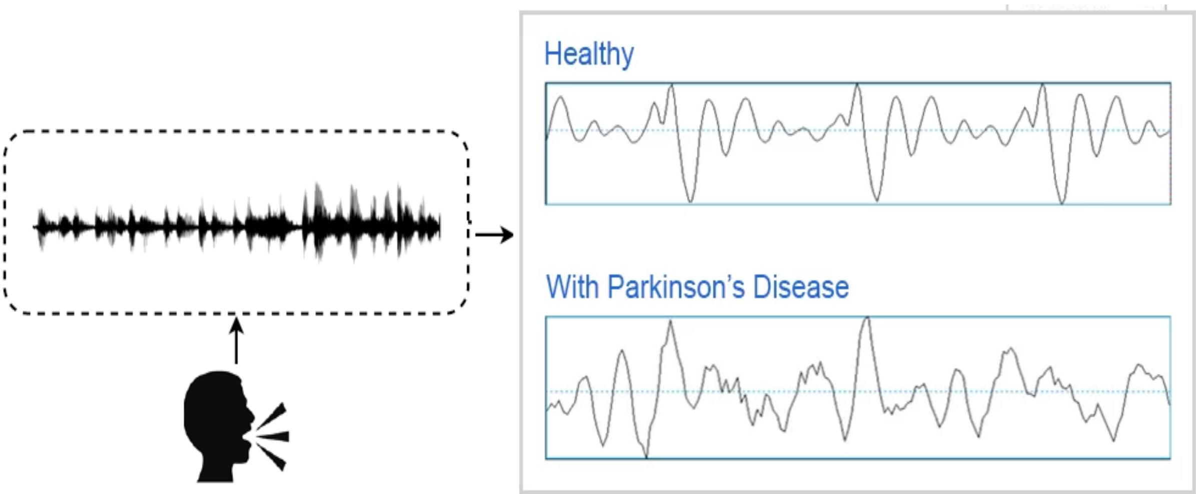


Fig (II.8): Example of a speech test [20]

II.5. Artificial Intelligence-Based Approaches for the Diagnosis of PD

Traditionally, diagnosis is based on clinical observation and is usually made by an experienced neurologist. However, there is a need for a more objective and automated approach to diagnosis. To this end, researchers have been exploring the use of Artificial intelligence (AI) algorithms for the diagnosis of PD.

Machine learning algorithms can be used to predict the progression of PD and its symptoms, which can help doctors make better decisions on treatment and disease management and detect early signs of PD, allowing for early diagnosis and treatment. However, machine learning algorithms have some limitations, and the accuracy of machine learning algorithms can be affected by the quality of the data used to train them. The results of machine learning algorithms are not always interpretable, making it difficult to explain why the algorithm made a certain decision. Additionally, deep learning algorithms can be used to learn features from signals or images associated with PD and accurately detect PD.[25]

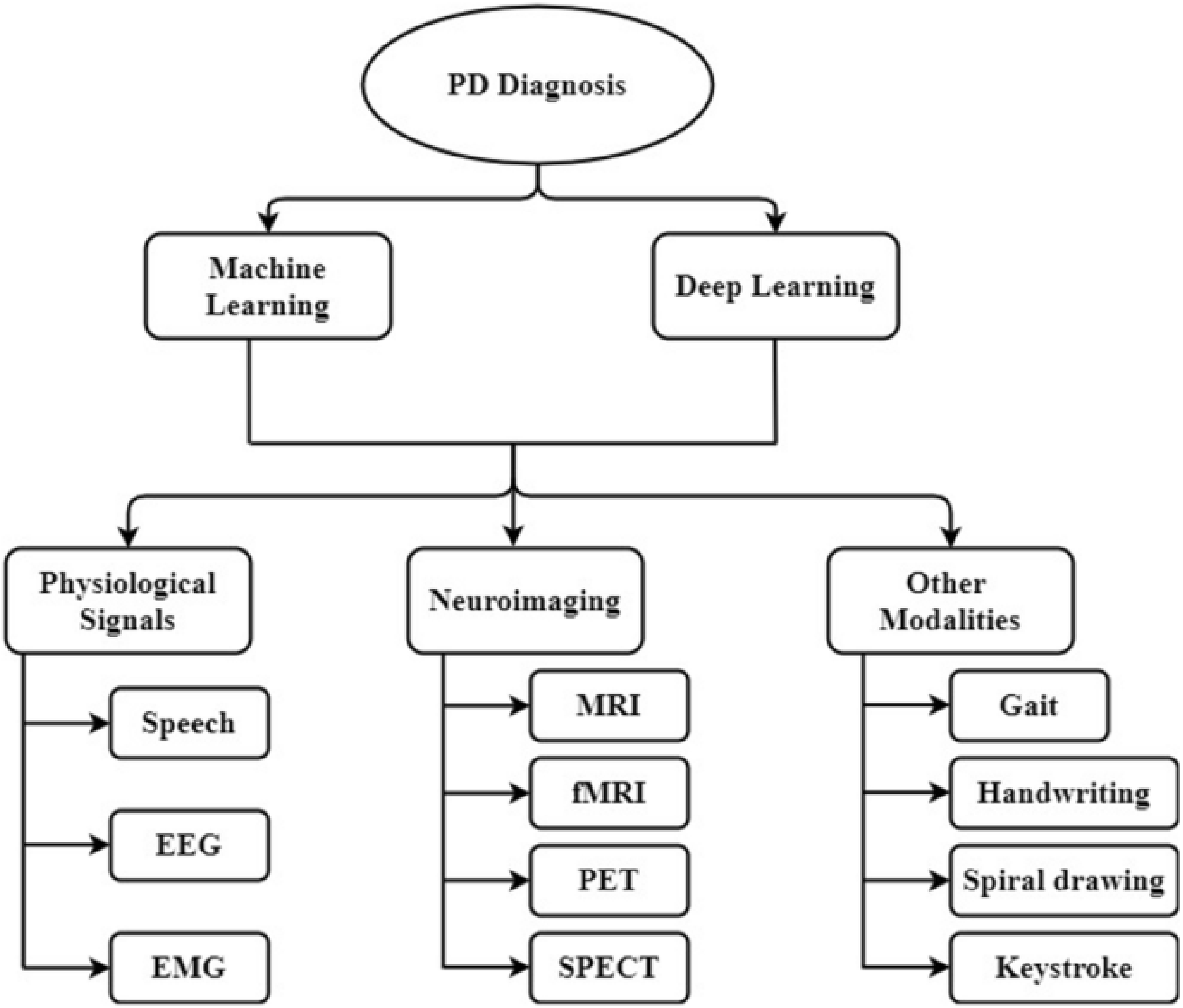


Fig (II.9): Artificial Intelligence-Based Approaches for the Diagnosis of PD[25]

II.5.1. Machine learning algorithms used to diagnose Parkinson's disease

Diagnosing Parkinson's disease (PD) using machine learning (ML) involves various techniques that can analyze patterns and make predictions based on medical data, such as voice recordings, gait analysis, and imaging data. Each algorithm has its unique strengths and can be chosen based on the specific requirements and characteristics of the dataset. **Fig II.10** presents some commonly used ML algorithms for diagnosing PD.

Various supervised machine learning (ML) techniques have been employed for the diagnosis of PD, each offering unique strengths and applications. Support Vector Machines (SVMs). Artificial Neural Networks (ANNs), K-Nearest Neighbors (KNN), Naive Bayes classifiers, Logistic Regression, Decision Trees, and CART (Classification and Regression Trees) are intuitive models that can handle various types of data, aiding in creating straightforward diagnostic models based on different criteria.[32]

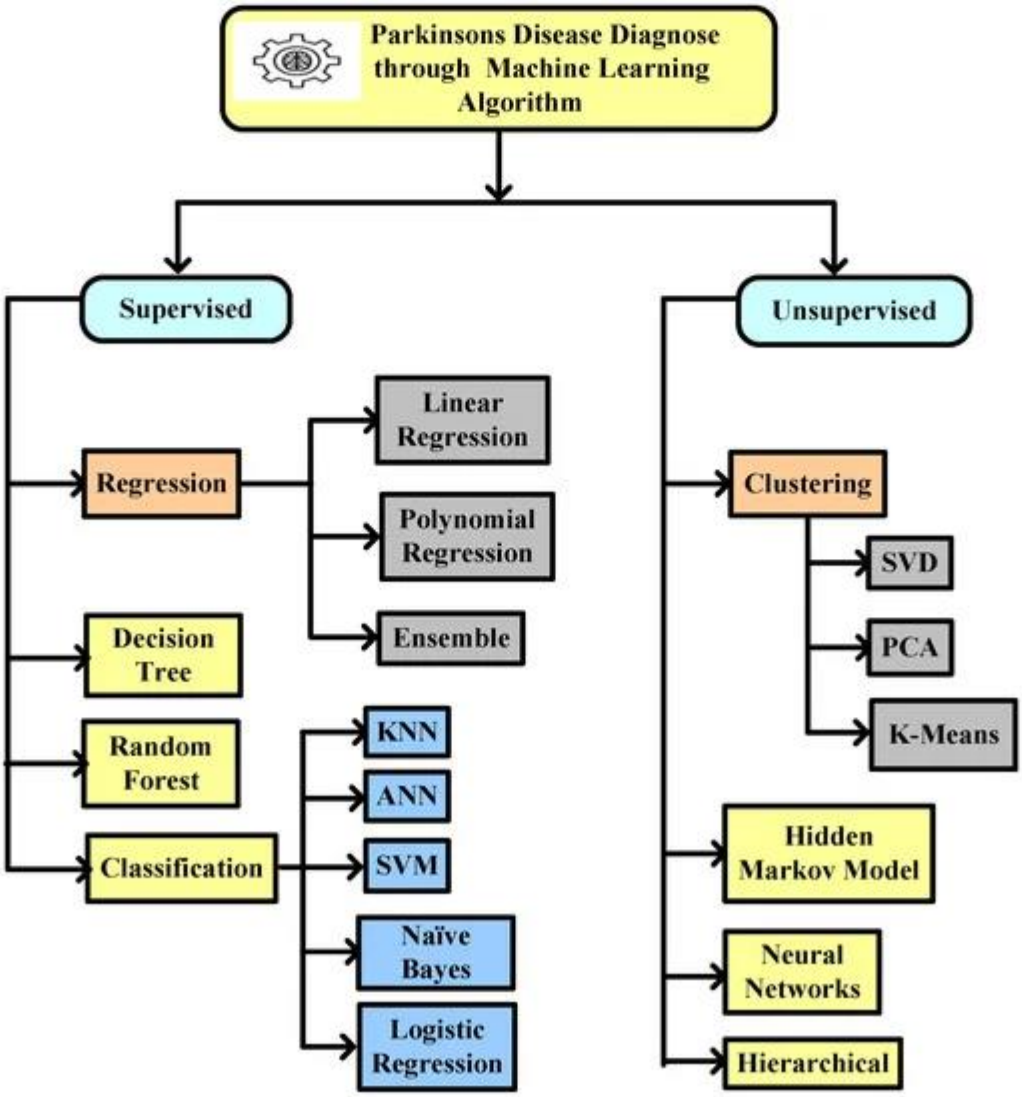


Fig (II.10): Machine learning algorithm used to diagnose Parkinson's disease.[32]

Various unsupervised machine learning (ML) techniques have been employed for the diagnosis of PD, offering unique advantages in analyzing complex medical data; Clustering algorithms such as K-means clustering and hierarchical clustering can group patients based on similarities in their symptoms and medical profiles, potentially revealing distinct subtypes of PD. Dimensionality reduction techniques such as Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and t-distributed Stochastic Neighbor Embedding (t-SNE) can help visualize and explore high-dimensional medical datasets, providing insights into the underlying structure of the data and potentially uncovering new patterns related to PD.

II.5.2. Deep learning algorithms used to diagnose Parkinson's disease

Various supervised deep learning (DL) techniques have been employed for the diagnosis of Parkinson's disease (PD), offering unique advantages in analyzing complex medical data. Convolutional Neural Networks (CNNs) have been particularly effective in analyzing medical imaging data, such as MRI scans or PET scans, to detect signs of PD-related brain changes. Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, are well-suited for analyzing sequential data, such as time-series data from sensors tracking a patient's movements, which can be indicative of motor symptoms of PD. Deep Belief Networks (DBNs) and Autoencoders have been used for feature learning and dimensionality reduction, respectively, to extract relevant features from high-dimensional medical data for PD diagnosis. Capsule Networks are also emerging as a promising approach for capturing hierarchical relationships in complex medical data related to PD. These supervised DL techniques complement traditional machine learning approaches and can significantly enhance the accuracy and efficiency of PD diagnosis.

II.5.3. PD with CNN using imaging dataset

Pereira investigated the effectiveness of Convolutional Neural Networks (CNNs) for diagnosing Parkinson's Disease (PD) using images of meanders and spirals. They compared various approaches, including a baseline Standard CNN and CNNs optimized with Bat Algorithm (BA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), and random search (RA).[12]

Their study utilized the extended "HandPD" dataset, comprising spiral and meander images at 256x256 pixel resolution. The dataset was split into 30% for training, 20% for validation, and 50% for testing.

Using the Wilcoxon signed-rank test, they found that for the meander dataset, CNNs with BA, PSO, and the standard CNN achieved the highest overall accuracies (79.62%, 75.76%, and 78.18%, respectively). BA showed the highest accuracy in classifying PD. Similarly, for the spiral dataset, BA, PSO, and the standard CNN achieved the highest accuracies (87.20%, 88.33%, and 89.55%, respectively), with BA also excelling in PD classification.

Their study confirmed that the spiral test posed greater difficulty for PD patients compared to the meander test, leading to more significant differentiation between healthy individuals and PD patients in spiral tests.

II.6. PD diagnosis problems

The literature review highlights several common challenges encountered by researchers in Parkinson's Disease (PD) diagnosis:

II.6.1. Difficulty in Early Symptom Detection

Identifying symptoms in the early stages of PD poses a significant challenge. Hand-drawn images, commonly used for diagnosis, may not suffice as Pereira et al. (2015) observed similarities in the hand-drawn exams of both healthy individuals and early-stage patients. This challenge is amplified in tests involving meander drawings, which are simpler than spiral drawings.[12,22,23]

II.6.2. Small, Biased, and Rare Datasets

Datasets available for PD diagnosis are often limited in size, biased, and scarce. This scarcity, coupled with the challenges in symptom detection, complicates diagnosis based solely on hand-drawn images. Utilizing tools like smart pens, as demonstrated by Pereira et al. (2016), allows for the extraction of additional features, such as motor features, which can aid in PD diagnosis.[23]

Table (II.1): The most consistent Handwriting datasets

Dataset Name	Size	Acquisition device	Tasks
PaHaW	37 PD 38 HC	Wacom Intuos 4M	-Spiral drawings -Repetition of ''l'', ''le'', ''les'', ''lektorka', ''porovnat'',''nepopadnout' ''tranvaj dnes uz nepo-jede''
HandPD	74 PD 18 HC	Bisp	-Spiral and meander drawing
NewHanPD	31 PD 35 HC	Bisp	-Spiral and meander drawing
ParkinsonHW	62 PD 15HC	Wacom Cintip 12 WX	Static spiral drawing, Dynamic spiral drawing, and stability test

II.6.3. Difficulty in Home Monitoring

Monitoring PD patients at home poses challenges due to the cost and availability limitations of at-home tools. addressed this challenge by developing a monitoring device capable of measuring dyskinesia, thereby assisting clinicians in managing medication regimens.[21]

These challenges underscore the need for innovative approaches and technologies to improve the accuracy and efficiency of PD diagnosis, particularly in the early stages, and facilitate effective monitoring of patients in home settings.

II.7. Conclusion

In this chapter, we have provided an overview of Parkinson's disease and explored how machine learning and deep learning techniques are being employed for its detection and diagnosis. Early and accurate diagnosis is crucial for effective management and treatment of the disease.

Chapter III

Chapter III: Results and discussions

III.1 Introduction

In this chapter, we delve into the evaluation process and the outcomes obtained for Parkinson's detection. The efficacy of the models is assessed and scrutinized through metrics such as Accuracy, Precision, and Recall.

In our evaluation, we employed a Kaggle datasets comprising hand drawings from both Parkinson's disease (PD) patients and healthy individuals.

III.2 Methodology

III.2.1. Database Description

The study's data was obtained from Kaggle's repository [7]. A total of 55 subjects participated, comprising 28 in the Control Group and 27 in the Parkinson Group. Each subject completed two tests: the Spiral drawing test and the Wave drawing test. The dataset consists of 204 spiral and wave images split into 72 training and 30 testing images from 102 spiral images, also the wave images are split into 72 training and 30 testing images. The data set is already labeled as healthy, Parkinson, spiral, and wave as shown in figure III.1 and Table III.1

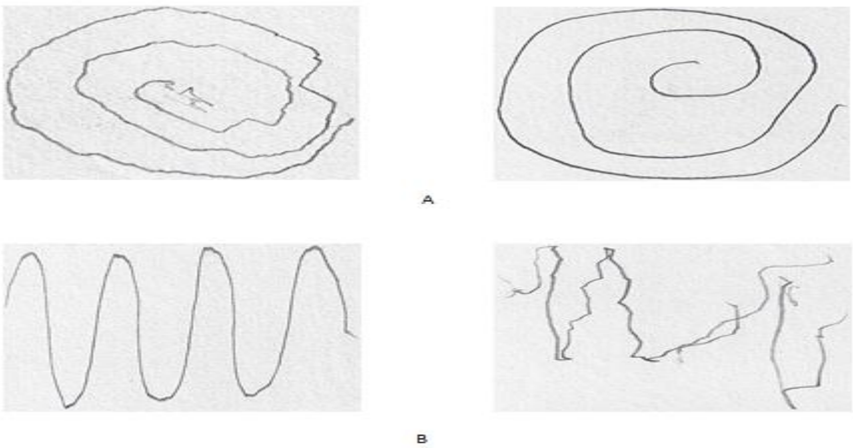


Figure (III.1): (A) Spiral and (B) wave drawings from Kaggle database

Table (III.1): Kaggle's repository dataset details

Type / Image	No. of Images in the Training set		No. of Images in the Test set		Total
	Healthy	**Parkinson**	**Healthy**	**Parkinson**	
Wave	36	36	15	15	102
Spira	36	36	15	15	102
Total	72	72	30	30	204

III.2.2. Proposed method

We propose employing 2D CNNs for feature extraction and then concatenating these features to pass to a classifier. This approach can improve the model’s ability to extract and utilize relevant features, leading to more accurate diagnoses. Our proposed approach involves three main steps; feature extraction using a pre-trained convolutional neural network, these features are then concatenated and passed to a classifier. We use fully ConnectedLayer and single layer classifier (softmax). The pre-trained CNN model is used to extract features by removing the final classification layer and using the rest of the network as a feature extractor.

The fusion of features from Spiral and Wave Diagrams is a crucial step in creating a comprehensive representation that captures the nuanced motor irregularities associated with Parkinson’s Disease. Combining features from these two distinct types of data enhances the diagnostic accuracy of machine learning models, such as the AlexNet Neural Network. Figure III.2, illustrates the complete system architecture with AlexNet of a general architecture as follows:

- Data Input: Hand drawings (spiral and wave diagrams).
- Feature Extraction:

Spiral Diagrams: Use pre-trained AlexNet to extract features from spiral diagrams.

Wave Diagrams: Use pre-trained AlexNet to extract features from wave diagrams.

- Feature Concatenation: Concatenate the features extracted from spiral and wave diagrams to create a combined feature representation.
- Classifier: Feed the combined features into a fully connected layers classifier.
- Output: The output of the classifier indicates the prediction for Parkinson’s disease diagnosis.

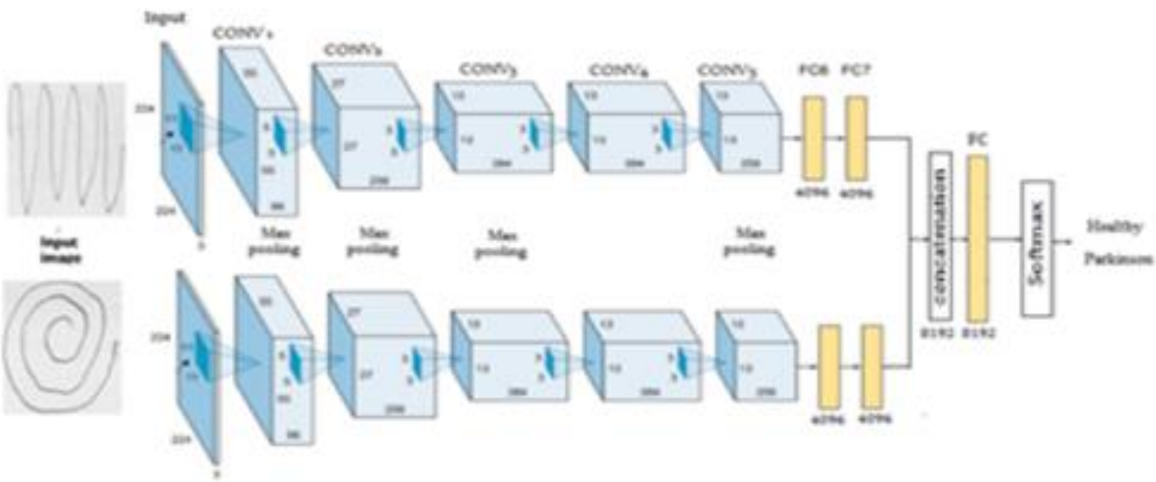


Figure (III.2): Proposed Methodology Architecture with pre-trained AlexNet.

III.2.3. Evaluation

We evaluated the performance of our proposed method using four metrics [26]: accuracy (Acc), sensitivity (SN, also known as recall (R)), and specificity (S).

III.3 Case Study 1: Results and discussion for Spiral Drawings

III.3.1. ResNet 50

Resnet 50 model was given a try in this project. The results achieved is tabulated in the below table and it is observed that the accuracy of the model is 90.00%, the confusion matrix from figure III.3.

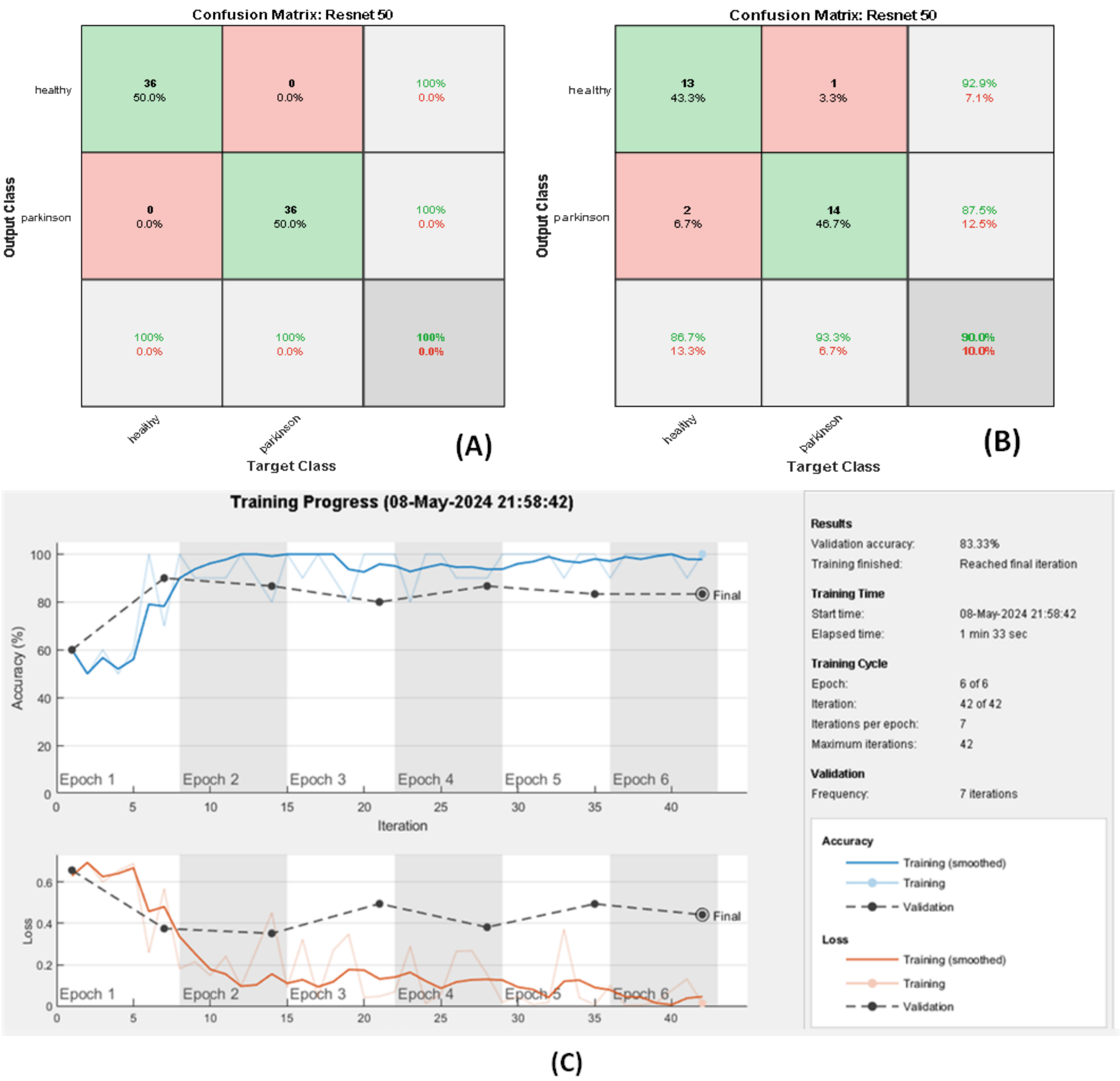


Fig (III.3): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of ResNet 50

III.3.2. Densenet 201

In this project, we experimented with the DenseNet-201 model. The results, as summarized in the table below, indicate that the accuracy achieved by this model matches that of ResNet-50, standing at 90.00%.

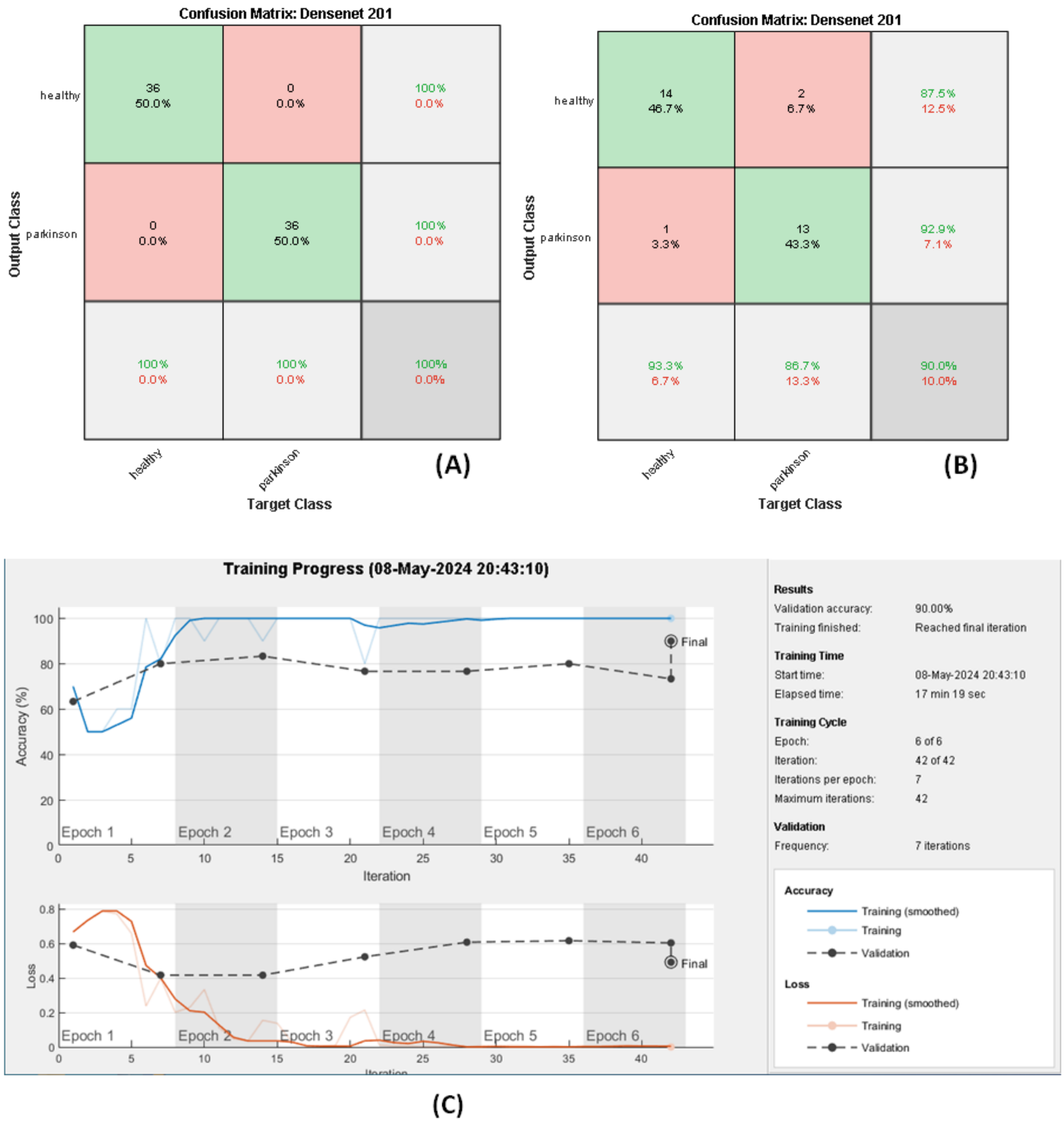


Fig (III.4): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of DenseNet201

III.3.3. AlexNet

AlexNet it provides an 83.33% result in terms of accuracy and this is lower than the previous results of DenseNet and ResNet. Figure 10 shows the graph of the train loss and the confusion matrix.

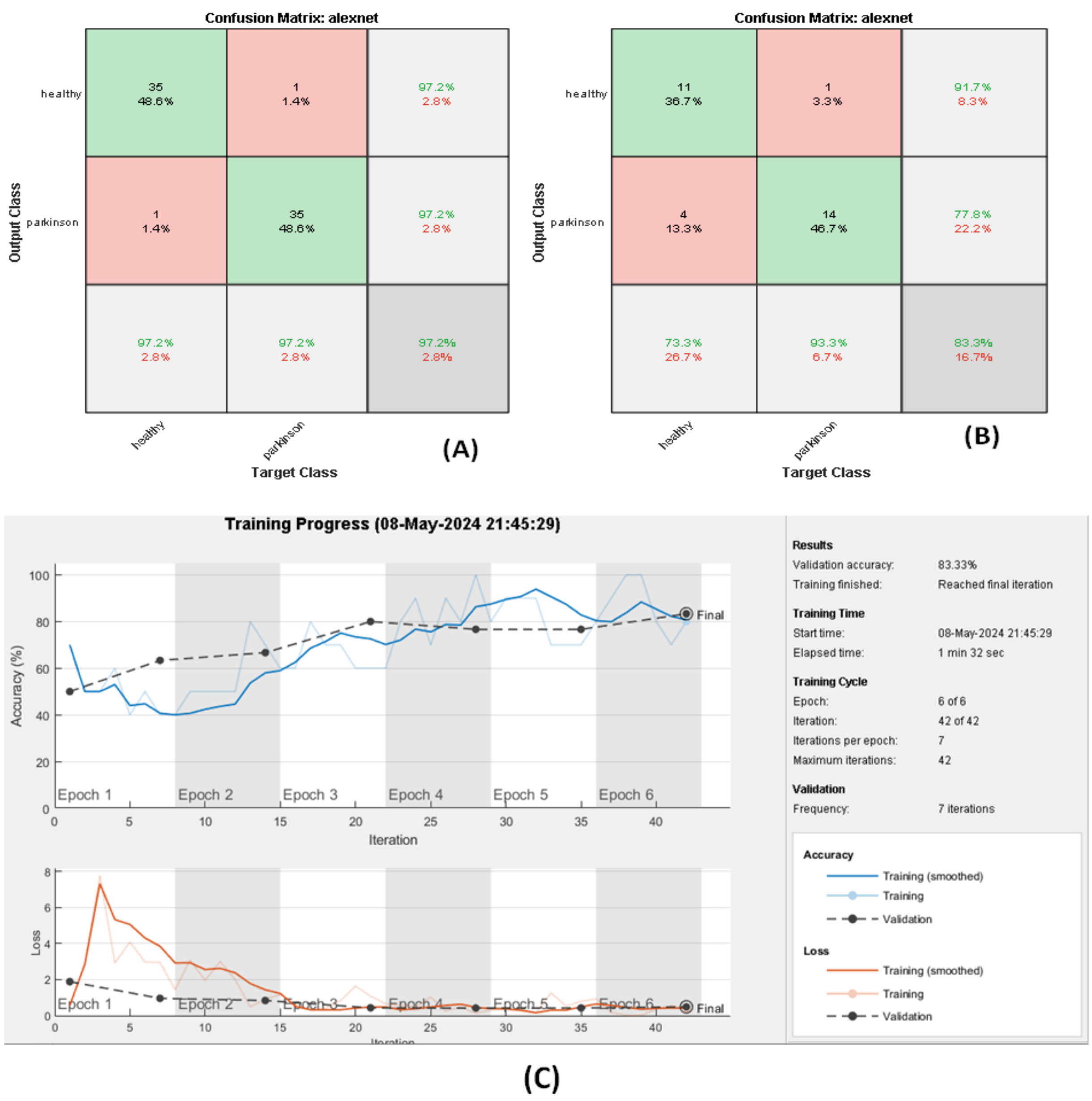


Fig (III.5): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of AlexNet

III.4. Case Study 2: Results and discussion for Wave Drawings

III.4.1. ResNet 50

When the ResNet50 was applied to wave data, we got 90% accuracy.

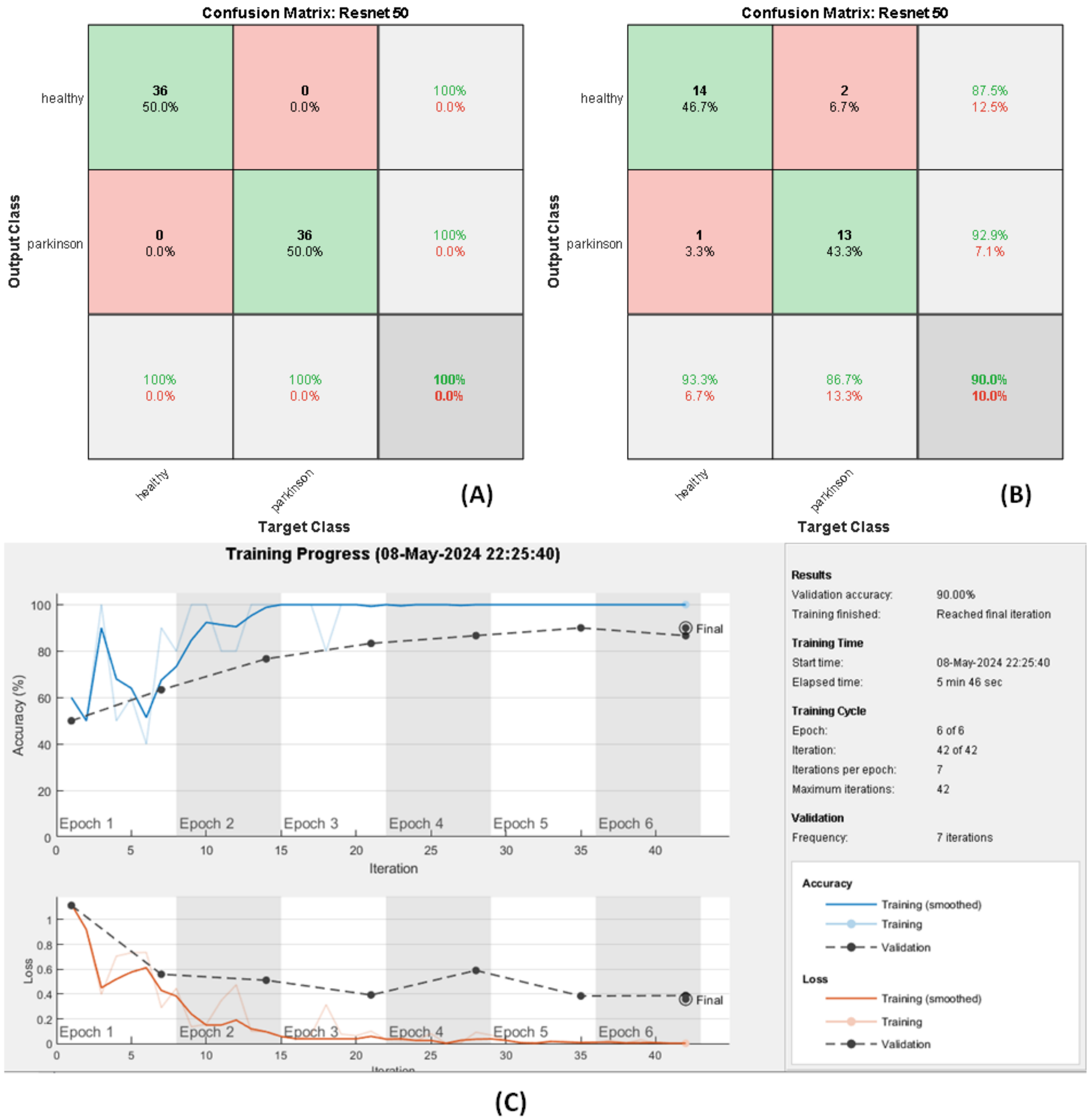


Fig (III.6): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of ResNet50

III.4.2. DenseNet 201

Applying DenseNet201 to the wave data yielded no improvement over ResNet50, with both models achieving an accuracy of 86.67%

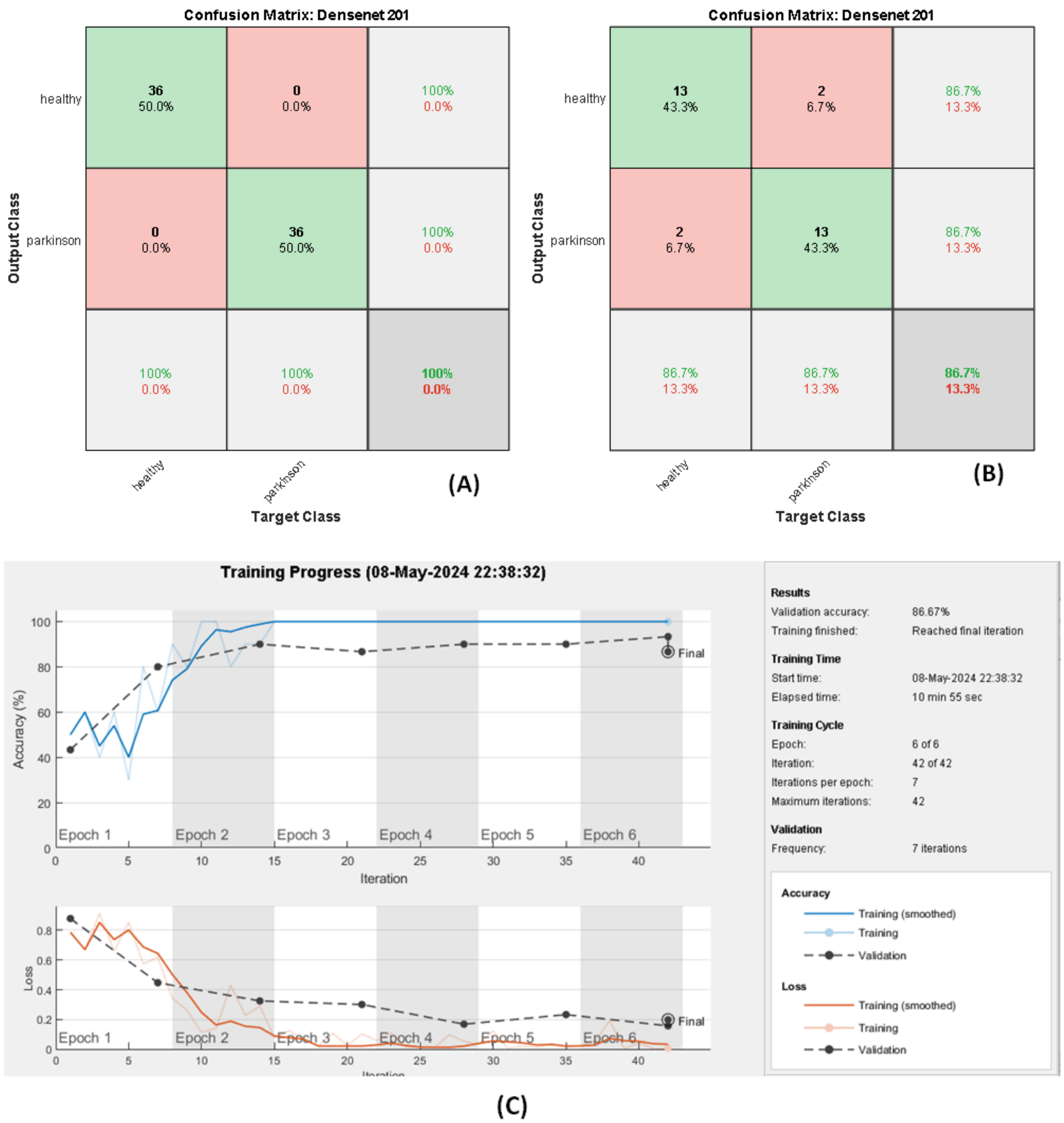
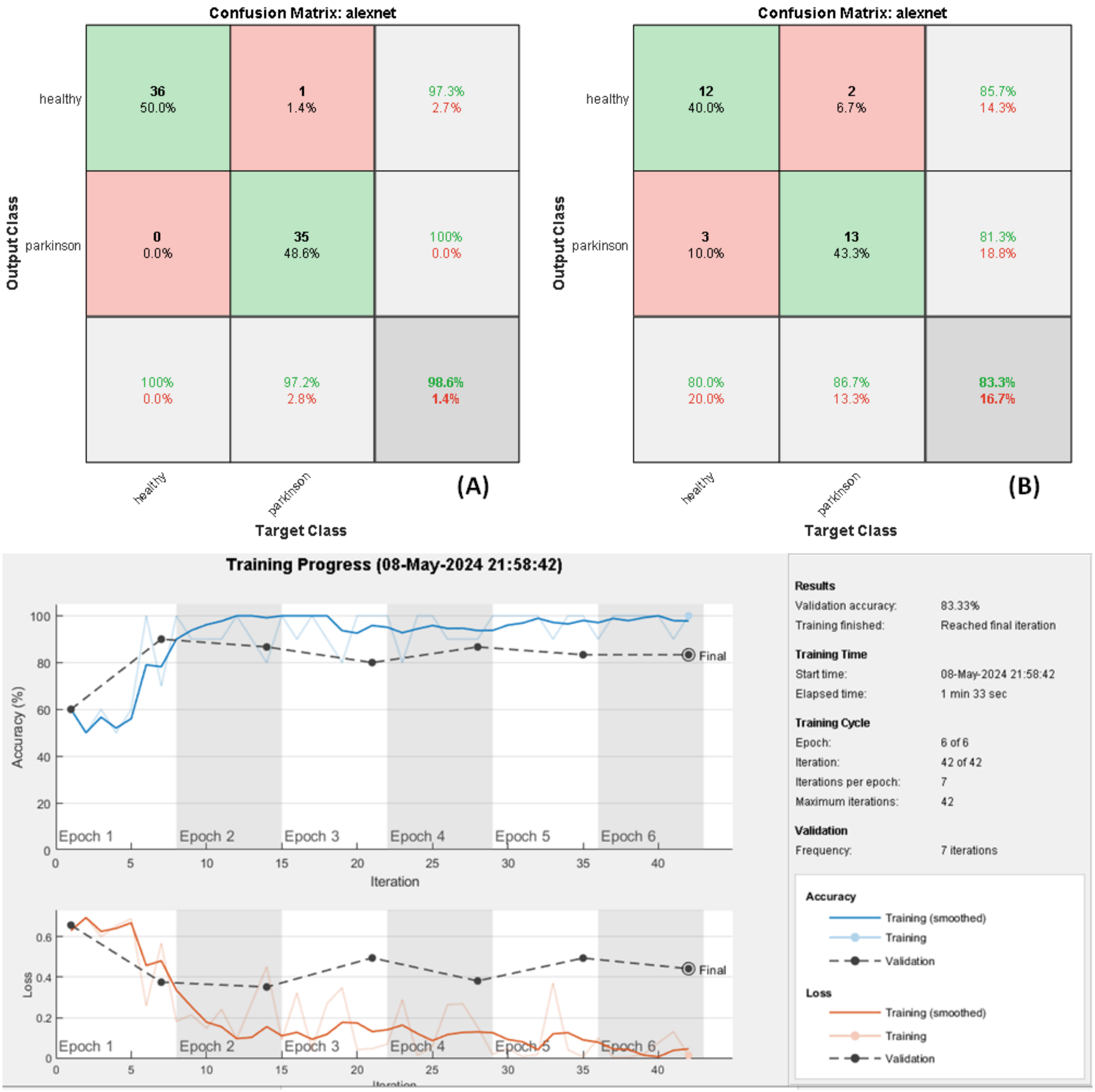


Fig (III.7): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of DenseNet201

III.4.3. AlexNet

Using AlexNet on the wave data did not yield any improvement over DenseNet, with an accuracy of 83.33%. Notably AlexNet was not convincing. Figure III.6 depicts the training loss and the confusion matrix generated for the AlexNet model on the wave data.



(C)

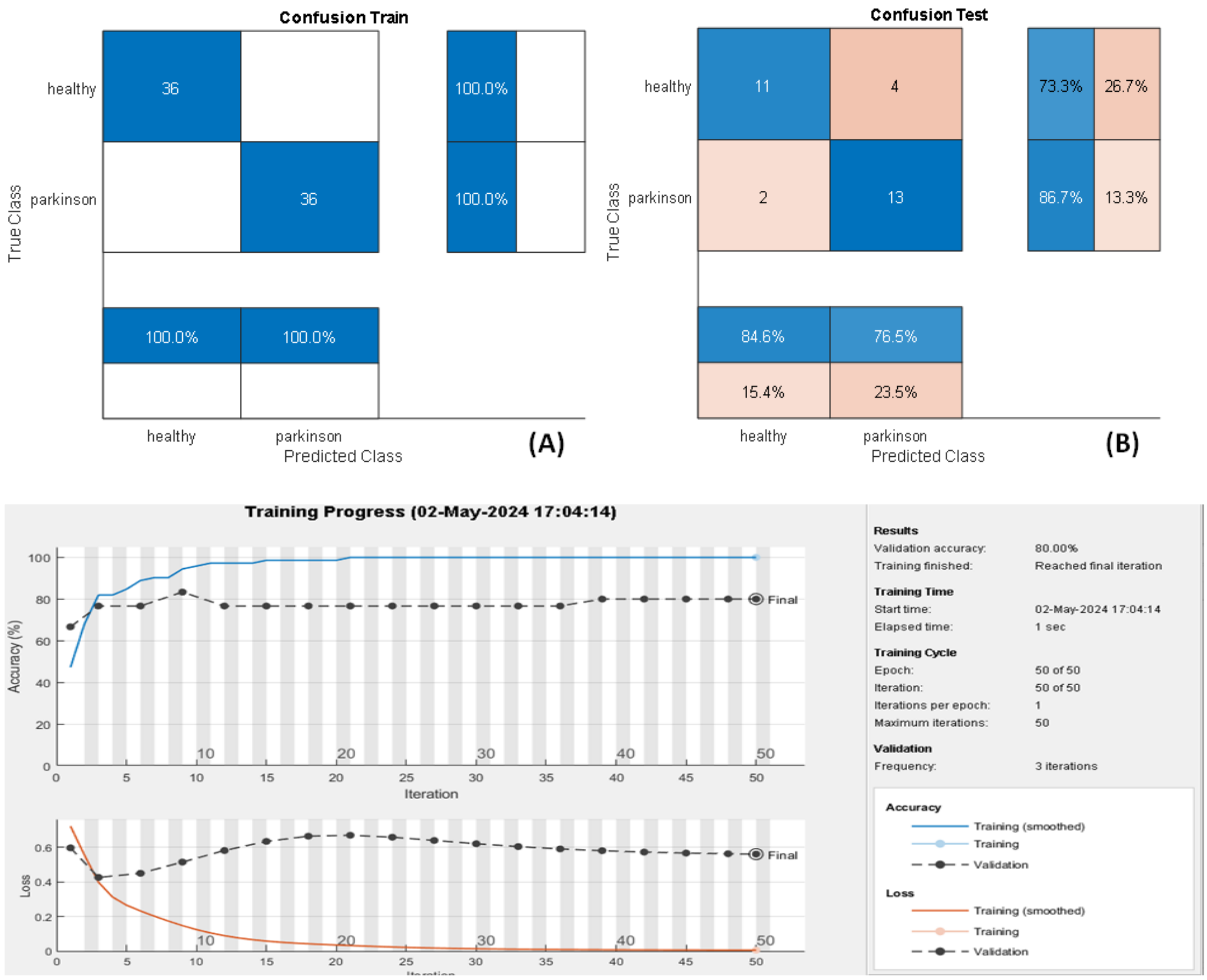
Fig (III.8): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of AlexNet

III.5. Case Study 3: Results and discussion for Spiral and wave drawings

In this case we use Proposed method, we extract each of the features of the Spiral and Wave drawings and then combine the features before classification.

III.5.1. ResNet 50

Resnet 50 when applied for spiral based data an accuracy of 80.00% is achieved as shown in the **Fig (III.9)** below:



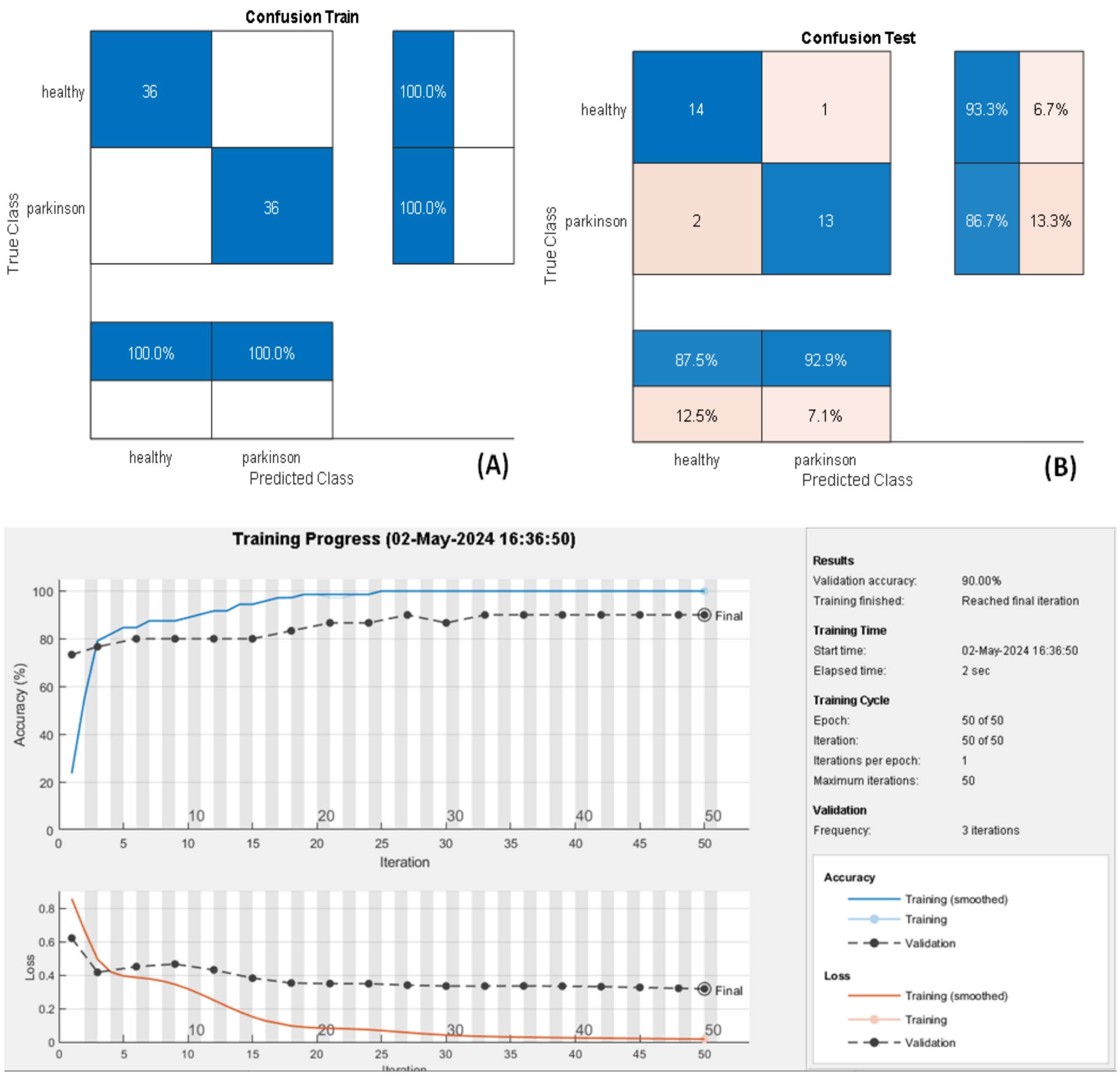
(C)

Fig (III.9): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of Resnet 50

By the results we can conclude that it is not a great model, as the sensitivity achieved is low.

III.5.2. DenseNet 201

Densenet 201 when applied for spiral based data an accuracy of 90.00% is achieved, results better than Resnet 50 as shown in FIGURE 2 below:



(B)

Fig (III.10): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of Densenet 201

III.5.3. AlexNet

Alexnet is the best CNN in this study in terms of accuracy where we got 96.67% as shown in the shapes at the bottom:

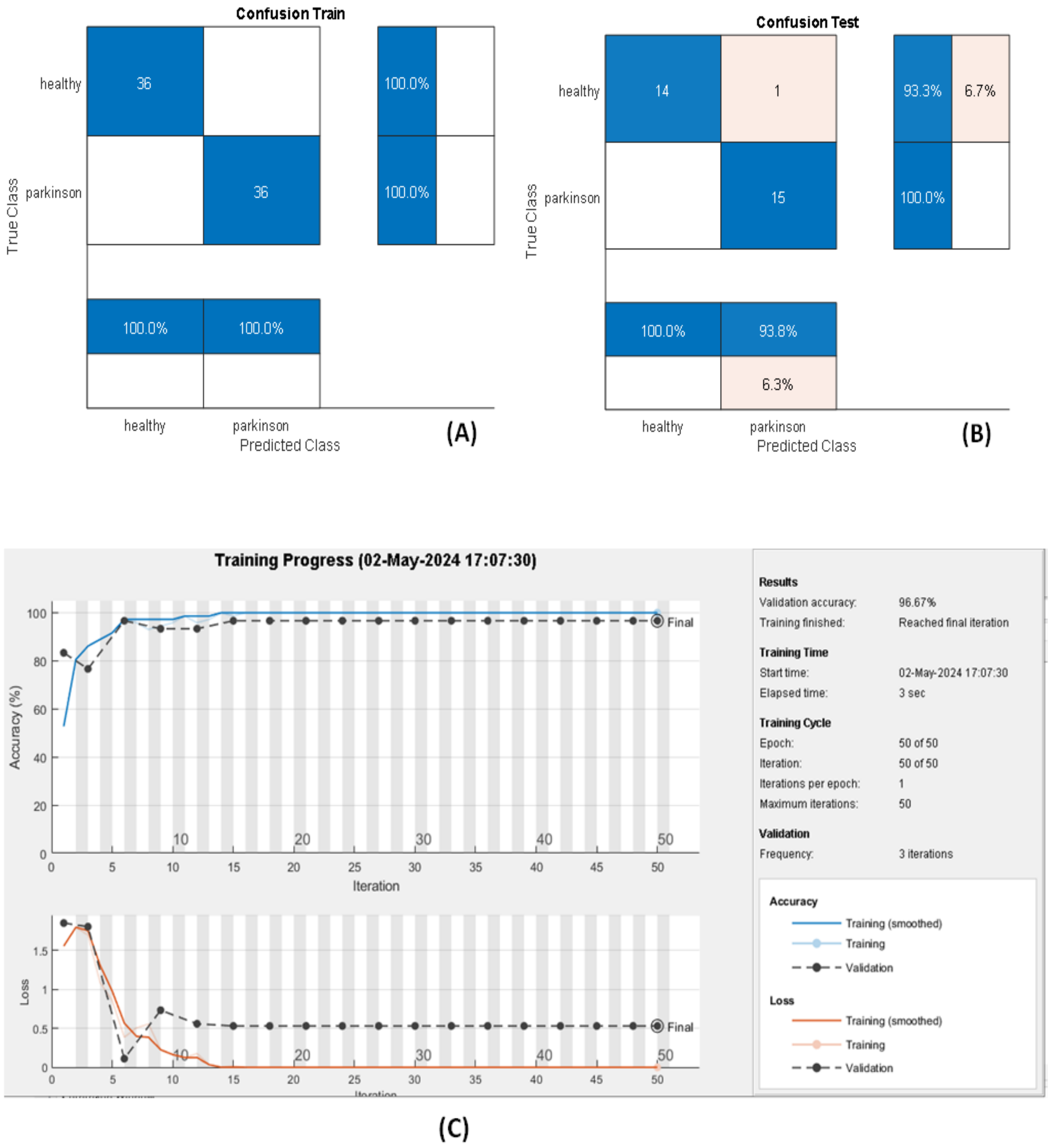


Fig (III.11): (A) Confusion matrix of train **(B)** Confusion matrix of test **(C)** Training process of AlexNet

III.5.4. Comparison of Developed Models for 3 Different Case Studies and with existing Models

Table III.2 provides a comparative analysis of the different models used in our research project, with a particular focus on ResNet 50, DenseNet 201 and AlexNet across different types of hand-drawn graphics: wave, spiral and a combination of both. Notably, AlexNet shows superior performance, especially in dealing with mixed data types, achieving impressive accuracy of 96% and sensitivity of 93%. In the context of medical diagnosis, allergies are of great importance because they mean the model's ability to accurately identify individuals with Parkinson's disease from healthy people.

As we note from table III.3, our proposed method is better than some previous studies.

Table (III.2): Comparison of different Cases studies

METHOD	DATA	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
ResNet 50	**Spiral**	90,00	92,9	87,5
DenseNet 201		90,00	87,5	92,9
AlexNet		83,33	91,7	77,8
ResNet 50	**Wave**	80,00	87,5	92,9
DenseNet 201		86,67	86,7	86,7
AlexNet		83,33	85,7	81,3
ResNet 50	**Fusion**	80,00	86,7	73,3
DenseNet 201		90,00	86,7	93,3
AlexNet		96,67	93,3	100

Table (III.3): Comparison Between Existing Models

METHOD	ACCURACY (%)	DATA	AUTHORS
Svm	67	Meander Sketches	Pereira et al .(2016) [33]
NB 34	78.9	Meander Sketches	Pereira et al . (2016) [33]
KNN	73.53	Spiral Skethes	Spadoto et al(2010) [35]
OCFA	88	Meander Skethes	Gupta et al. (2018) [34]
ANN + MLP	67.84	Spiral Skethes	Spadoto et al. (2010) [35]
AlexNet	96.67	Spiral+Wave Skethes	This study

III.6 Conclusion

This chapter introduces a novel method for detecting Parkinson's disease using deep convolutional neural networks based on the AlexNet / resNet 50 / denceNet 201 architectures. The approach focuses on integrating features extracted from both spiral and wave drawing patterns, obtained from patients with Parkinson's disease and healthy individuals. Combining these features could potentially improve the accuracy of detection. The fusion of features from both spiral and wave drawing patterns seems to be a promising strategy for enhancing the detection performance. Our approach with AlexNet achieves an accuracy of 96.67% on the test set, outperforming existing methods. This study contributes to the advancement of PD detection methodologies, highlighting the potential of CNNs and multimodal data integration in medical diagnosis.

General Conclusion

This research introduces a novel approach to Parkinson's disease detection by leveraging drawing patterns, which can provide valuable insights into early signs of the condition, particularly in hand motor functionality. This method offers an inexpensive, easily accessible, and remote evaluation process. The primary contribution lies in utilizing deep neural network and computer vision techniques to analyse these drawing patterns.

The study evaluates the detection of Parkinson's disease using spiral and wave-based datasets, as well as a combination of both, employing Residual Networks (ResNet 34, DenseNet 201, and AlexNet). While ResNet50 and DenseNet 201 models fell short of achieving the desired accuracy and sensitivity, AlexNet emerged as the top performer, particularly in handling fused (Wave + Spiral) data.

The results underscore the potential benefits of combining different types of data for improved detection accuracy. Consequently, all objectives and sub-objectives of the research are fulfilled. This approach holds promise for remote and accessible detection and treatment of Parkinson's patients, thereby conserving resources and enhancing accessibility, especially in rural and remote regions where access to healthcare services is limited.

In future endeavours, expanding the dataset size with a greater number of cases can enhance the accuracy of deep neural networks and mitigate overfitting issues. Additionally, incorporating new features such as speech and developing a multi-modal system could further enhance the accuracy of Parkinson's diagnosis.

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