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**Final Project Report**
**For obtaining the Master's degree in Computer Science**

**Theme:**

# Soil recognition and features measurement using AI

**Presented by:**

Ferhi Aya

**Supervisor:** Prof. Amran Laila.

College year: 2022 | 2023

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## *Dedication*

***Praise be to Allah and thanks to Allah***

*To my struggling family: "My mother, my father, and my sisters, Soumia, Nour, Hanine and Chahed"*

*To the pure soul of my grandfather "Noah", my dear grandmother, my aunts and my uncle, each in his name*

*To the soul of my dear grandmother "Saada ben zawi" and the soul of my dear grandfather "Ahmed Gherissi" and my aunts and uncles, each in his name*

*To my niece Safwa| her aunt's beloved.*

*To my friends, my sisters Rehab Kaddouri and Badis Sakina*

***To everyone I love, thank you all from the heart***

# Acknowledgment

I wanted to dedicate this thanks and appreciation to my supervising professor,because she have a great and very great credit in my work , so I thank you from the heart, Dr. Laila Amrane, for all the advice and guidance that you provided throughout the preparation of the memorandum.

I also want to thank the INRA Sidi El Mahdi experimental station for opening the doors to our questions and providing us with everything they could provide for the success of this research.

# Abstract

Soil plays an important role in the quality of agricultural crops, especially since we are in an era in which the agricultural sector occupies a great importance not only from the side of the economy, but also from the side of achieving food sufficiency, so if the type of the soil is not appropriate, then the product will not be of the required quality. In our research, we wanted to help every farmer and peasant and everyone interested in this field by developing a website that allows soil classification (initially five types) by including a picture of the soil to know its type. The classification process was carried out using deep learning exactly Proposed CNN model, which had the highest accuracy(86%) after comparing it with 3 other models, VGG(80%), ResNet(79%), and MobileNet(76%). In the end, after the classification is done, the most important characteristics (six characteristics) of that soil are presented, whitch is temperature, Ph,Porosity ,texture,color ,density.


**Keywords:** Artificial Intelligence ,Deep Learning , CNN, Proposed CNN, VGG16,Res Net ,Mobile Net.

# ملخص

تلعب التربة دورا هاما في جودة المحاصيل الزراعية خاصة وأننا في عصر يحتل فيه القطاع الزراعي أهمية بالغة ليس فقط من جانب الاقتصاد وانما أيضا من جانب تحقيق الاكتفاء الغذائي، فاذا كانت نوعية التربة غير ملائمة فلن يكون المنتوج بالجودة المطلوبة. في بحثنا هذا أردنا مساعدة كل فلاح ومزارع وكل مهتم بهذا المجال من خلال وضع موقع ويب يسمح بتصنيف التربة (مبدئيا خمسة أنواع) عن طريق ادراج صورة للتربة المراد معرفة نوعها. تمت عملية التصنيف باستخدام أحد نماذج التعلم العميقCNN ، بالتحديد «Proposed CNN» الذي كانت له اعلى نسبة دقة بعد المقارنة بينه وبين 3 نماذج أخرى (Mobile Net، Res Net،VGG-16,Proposed CNN ) والتي أخذت نسبة دقة (76,79,80,86) على التوالي. في الأخير وبعد ان تم التصنيف عرضنا اهم الخصائص (ستة خصائص) لنوع التربة المطلوب هذه الخصائص متمثلة في: المسامية، الكثافة، درجة الحرارة، درجة الحموضة، اللون، النسيج(القوام).

الكلمات المفتاحية: الذكاء الاصطناعي، التعلم العميق، CNN، Proposed CNN، VGG-16، Mobile Net,Res Net .

# Abstrait

Le sol joue un rôle important dans la qualité des cultures agricoles, d'autant plus que nous sommes à une époque où le secteur agricole occupe une grande importance non seulement du côté de l'économie, mais aussi du côté de la réalisation de l'autosuffisance alimentaire, donc si le type de sol n'est pas approprié, le produit ne sera pas de la qualité requise. Dans notre recherche, nous avons voulu aider chaque agriculteur et paysan et toute personne intéressée par ce domaine en développant un site internet qui permet de classer les sols (initialement cinq types) en incluant une photo du sol pour connaître son type. Le processus de classification a été effectué en utilisant l'apprentissage en profondeur exactement CNN proposé, qui avait la plus grande précision (86%) après l'avoir comparé avec 3 autres modèles, VGG(80%), ResNet(79%) et MobileNet( 76%). En fin de compte, une fois la classification effectuée, les caractéristiques les plus importantes (six caractéristiques) de ce sol sont présentées, à savoir la température, le pH, la porosité, la texture, la couleur et la densité.


**Les mots cles:**Artificial Intelligence ,Deep Learning , CNN, Standard CNN, VGG16,Res Net ,Mobile Net.

# Introduction

Soil is the layer that covers the surface of the earth from farms, fields, forests, deserts, and many others, where soil can be the seat of life for different plants, and this is called agricultural soil, and it can also be used in other fields such as construction, and here it is called non-arable soil. Soil contains several types such as sand, clay, etc. This is what makes us ask several questions if we come across a certain soil, what type of soil is this? Is it porous soil or not, and is it suitable for growing rice, for example? And many other questions, and to answer all these questions, a soil expert must be consulted to answer these questions after touching, examining and analyzing the soil, and it may take hours or even days, especially with the lack of experts in this field. And because we are in an era where artificial intelligence has prestige and a heard word, we wanted to hire it as a soil expert, but with high speed, good accuracy, and without touching the soil. How will this happen? We will learn more about it in this research.

In the **first chapter,** we will discuss the most important definitions that we need to get a good start in this research, so we will learn about artificial intelligence, machine learning,Neural Networks, and deep learning.

In the **second chapter**, we will understand and analyze the model that we will use to classify soils and their types, and in the **third chapter** we will compare these types to choose the best and adopt them in our soil classification.

# Chapter 1

# General concepts

**Introduction:**

In this chapter, we will discuss the most important concepts that help us understand our subject, starting hierarchically with: Artificial intelligence, Machine learning, neural network, finally deep learning.

There are relation between this subject shown in Figure1.1

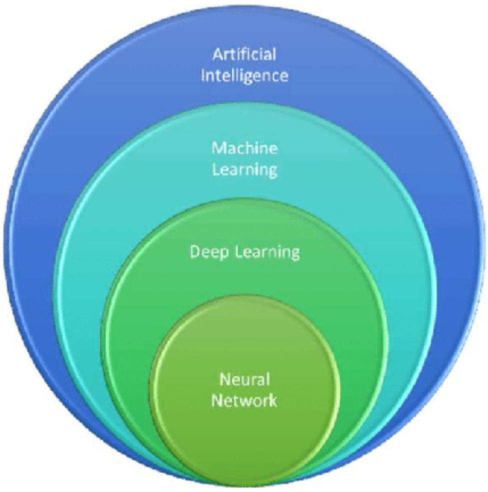



Figure 1.1: the relation between artificial intelligence, machine learning, Artificial Neural Network and deep learning [1]

## 1.1 Artificial Intelligence

Artificial Intelligence is defined as an integration of computer science and physiology intelligence in simple language is the computational part of the ability to achieve goals in the world. Intelligence is the ability to think to imagine creating memorizing and understanding, recognizing patterns, making choices adapting to change and learn from experience. Artificial intelligence concerned with making computers behave like humans.

AI tries to solve the complex problems in more human and in much less time than a human takes. Hence it is called as Artificial Intelligence. Artificial intelligence can be divided into two parts according to philosophy of AI:

1. Strong AI
2. Weak AI [4]

According to weak AI, the principal value of the computer in the study of the mind is that it gives us a very powerful tool. For example, it enables us to formulate and test hypotheses in a more rigorous and precise fashion. But according to strong AI, the computer is not merely a tool in the study of the mind; rather, the appropriately programmed computer really is a mind, in the sense that computers given the right programs can be literally said to understand and have other cognitive states. In strong AI, because the programmed computer has cognitive states, the programs are not mere tools that enable us to test psychological explanations; rather, the programs are themselves the explanations[14]. more details in Table 1.1

| | Strong artificial intelligence | Weak artificial intelligence |
|---|---|---|
| Definition | - The form of artificial intelligence, which has the same intellectual abilities as human, or even surpasses him in it. | - Weak Al is generally developed or used for specific application domains.<br>- In a standard work on artificial intelligence, this is formulated as follows:<br>”The assertion that machines could possibly act intelligently (called, weakness, act as if they are intelligent) is called the, weak Al’ hypothesis |
| Capabilities and domains | - Logical thinking.<br>- Making decision in case of uncertainty.<br>- To plan.<br>- To learn.<br>Communication in natural language.<br>Use all these abilities to achieve a common goal. | - Expert systems.<br>- Navigation systems.<br>- Voice recognition.<br>- Character recognition.<br>- Suggestions for corrections in searches. |

Table 1.1: Strong VS Weak AI

Most references to AI are now often used as an interchangeable term with ‘machine learning’ or ‘deep learning’, the latter being a specific form of machine learning [15] . So, what is machine learning and deep learning?

## 1.2 Machine learning:

Machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment [16]. Machine Learning relies on different algorithms to solve data problems. Data scientists like to point out that there's no single one-size-fits-all type of algorithm that is best to solve a problem. The kind of algorithm employed depends on the kind of problem you wish to solve, the number of variables, the kind of model that would suit it best and so on. The main advantage of using machine learning is that, once an algorithm learns what to do with data, it can do its work automatically [17]. Supervised Learning, Unsupervised Learning, and Reinforcement Learning are the three major kinds of ML.[18]

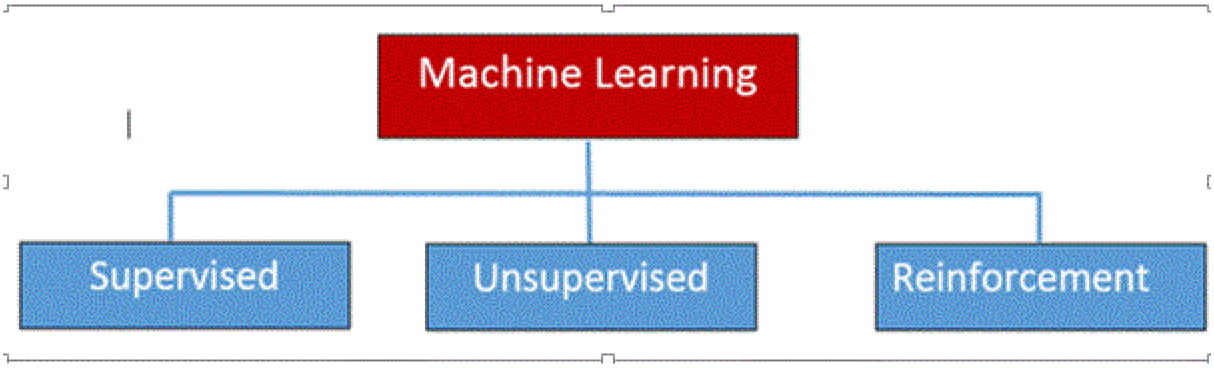



Figure 1.2: Types of machine learning

### 1.2.1 Supervised learning:

the machine is taught by example. The operator provides the machine learning algorithm with a known dataset that includes desired inputs and outputs, and the algorithm must find a method to determine how to arrive at those inputs and outputs. While the operator knows the correct answers to the problem, the algorithm identifies patterns in data, learns from observations and makes predictions. Two distinct types of learning: classification and regression[18]

1. **Classification:**

   In classification tasks, the machine learning program must draw a conclusion from observed values and determine to what category new observations belong. For example, when filtering emails as 'spam' or 'not spam', the program must look at existing observational data and filter the emails accordingly[19]

2. **Regression:**

   In regression tasks, the machine learning program must estimate – and understand – the relationships among variables. Regression analysis focuses on one dependent variable and a series of other changing variables – making it particularly useful for prediction and forecasting [19].

As example of supervised machine learning algorithms: Decision Tree, Naive Bayes, Support Vector Machine….

### 1.2.2 Unsupervised learning:

It refers to how to learn by yourself, by discovering and adopting, depending on the input model. In this learning, the data is divided into different clusters and this learning is called the classification algorithm. This is the task of machine learning to infer a function that describes the hidden structure of ”unlabeled” data. Because the examples specified to the learner are not labeled, there is no evaluation of the accuracy of the structure generated by the appropriate algorithm,[20] entails two distinct types of learning: clustering and association.

1. **Clustering:**

   Clustering is an important concept when it comes to unsupervised learning. It mainly deals with finding a structure or pattern in a collection of uncategorized data. Unsupervised Learning Clustering algorithms will process your data and find natural clusters (groups) if they exist in the data. You can also modify how many clusters your algorithms should identify. It allows you to adjust the granularity of these groups [21]

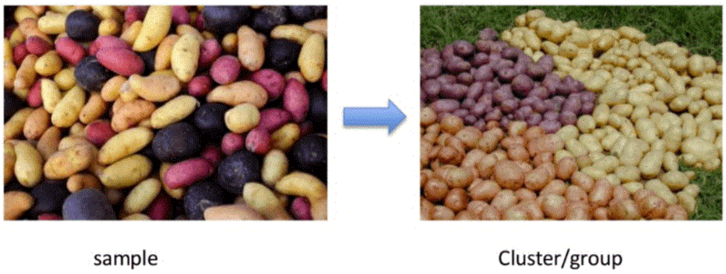



Figure 1.3: An image showing results of clustering [2]

2. **Association:**

   An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database. It determines the set of items that occurs together in the dataset. Association rule makes marketing strategy more effective. Such as people who buy X item (suppose a bread) are also tend to purchase Y (Butter/Jam) item. A typical example of Association rule is Market Basket Analysis. As example of unsupervised machine learning algorithms: K-Means Clustering[21]

### 1.2.3 Reinforcement:

Reinforcement learning (RL) is defined as a Machine Learning method that is concerned with how software agents should take actions in an environment.

Two types of reinforcement learning methods are:

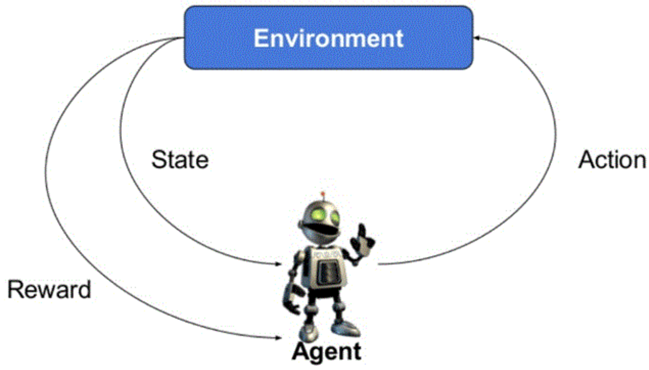



Figure 1.4: Typical RL scenario [3]

1. **Positive:**

   It is defined as an event, that occurs because of specific behavior. It increases the strength and the frequency of the behavior and impacts positively on the action taken by the agent. This type of Reinforcement helps you to maximize performance and sustain change for a more extended period. However, too much Reinforcement may lead to over-optimization of state, which can affect the results.

2. **Negative:**

   Negative Reinforcement is defined as strengthening of behavior that occurs because of a negative condition which should have stopped or avoided. It helps you to define the minimum stand of performance. However, the drawback of this method is that it provides enough to meet up the minimum behavior. Machine Learning can be a Supervised or Unsupervised or Reinforcement So If we have lesser amount of data and clearly labelled data for training, opt for Supervised Learning. Unsupervised Learning would generally give better performance and results for large data sets. If we have a huge data set easily available, the option is deep learning techniques[17].

## 1.3 Artificial Neural Networks(ANN)

Artificial neural networks (ANNs) are biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An ANN is formed from hundreds of single units, artificial neurons or processing elements (PE), connected with coefficients (weights), which constitute the neural structure and are organized in layers. The power of neural computations comes from connecting neurons in a network. Each PE has weighted inputs, transfer function and one output. The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself.

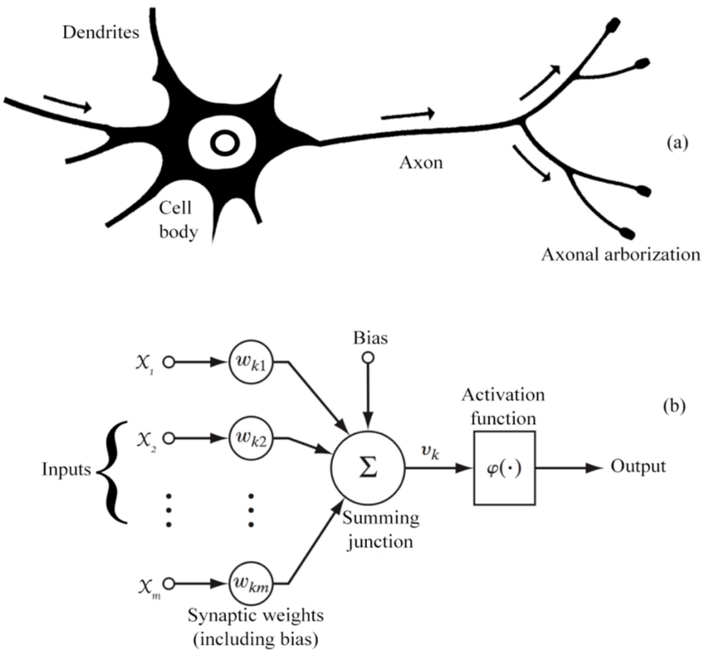



Figure 1.5: A comparison between biological neural network and Artificial Neural Network [4]

The weights are the adjustable parameters and, in that sense, a neural network is a parameterized system. The weighed sum of the inputs constitutes the activation of the neuron. The activation signal is passed through transfer function to produce a single output of the neuron. Transfer function introduces non-linearity to the network. During training, the inter-unit connections are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained and tested it can be given new input information to predict the output. Many types of neural networks have been designed already and new ones are invented every week but all can be described by the transfer functions of their neurons, by the learning rule, and by the connection formula .[22] Based on the following statement" All of deep learning is neural network but not vice versa " let's discover what means deep learning.

## 1.4 Deep learning:

It is a sub-field of machine learning that is based on learning several levels of representations, corresponding to a hierarchy of features or factors or concepts, where higher-level concepts are defined from lower-level ones, and the same lower level concepts can help to define many higher-level concepts. Deep learning is part of a broader family of machine learning methods based on learning representations. An observation (e.g., an image) can be represented in many ways (e.g., a vector of pixels), but some representations make it easier to learn tasks of interest (e.g., is this the image of a human face?) from examples, and research in this area attempts to define what makes better representations and how to learn them.[23]

**Conclusion:**

At the end of this chapter, we have taken a simple overview of artificial intelligence, machine learning, Artificial Neural Network and deep learning, and we have been able to understand the relationship between them. In the next chapter, we will discuss in depth the most important type of deep learning, which is the CNN model.

# Chapter 2

# Convolutional Neural Network model

**Introduction**

In this chapter, we will explain the most important type of deep learning, which is CNN. In addition, we will explain three of its types (which are of interest to us in our research) in a theoretical way.

## 2.1 Convolutional Neural Network

In deep learning, a convolutional neural network (CNN/ConvNet) is a class of deep neural networks, most commonly applied to analyze visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics convolution is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other [24]

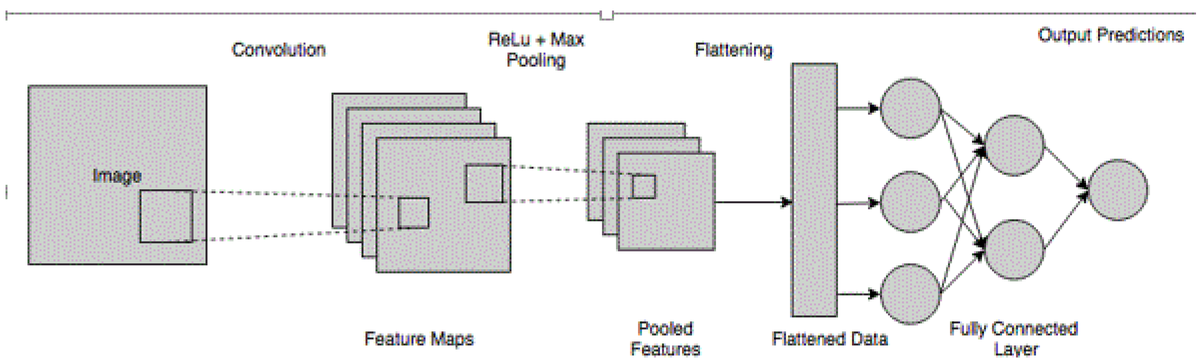



Figure 2.1: CNN model architecture [5]

## 2.2 How does it work?

Before we go into how the CNN model works in image classification, let's do some basic definitions such as defining an image and how it is represented.

The RGB image "Red, Green, Blue" (the color image) is a matrix of pixel values that has three levels, while the grayscale image has the same definition as the color image, but it is one level. A CNN model typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer [25]

1. **convolutional layer:**

   The convolutional operations are applied on the input data and then the outputs are sent to the next layer. An example of a convolutional operation is shown in Figure 2.2. Each neuron of the convolutional layer receives only a small portion of the outputs of the previous layer after convolving them with some "kernel." The group of output values a neuron can see is called the "receptive field" of that neuron[7].

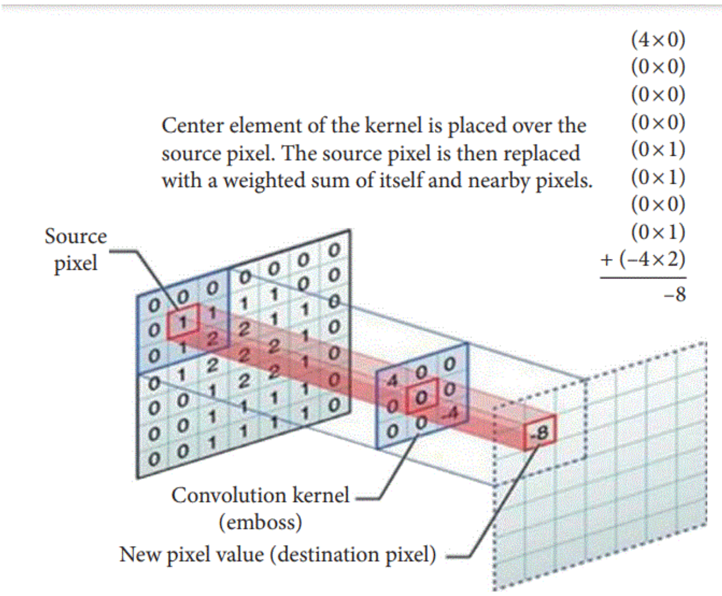



Figure 2.2: Convolution layer slides the filter over a given input. Output is the summation of an element by the element matrix multiplication of the filter and receptive field [6]

2. **Pooling layer:**

   The second main structure is the "pooling layer." It combines each group of the outputs of the previous layer into a single neuron. There are two common variations of pooling operations: average pooling and max pooling (Fig 2.3). An average pooling layer averages its input values by taking the mean of them. On the other hand, max pooling takes the biggest value. [7].

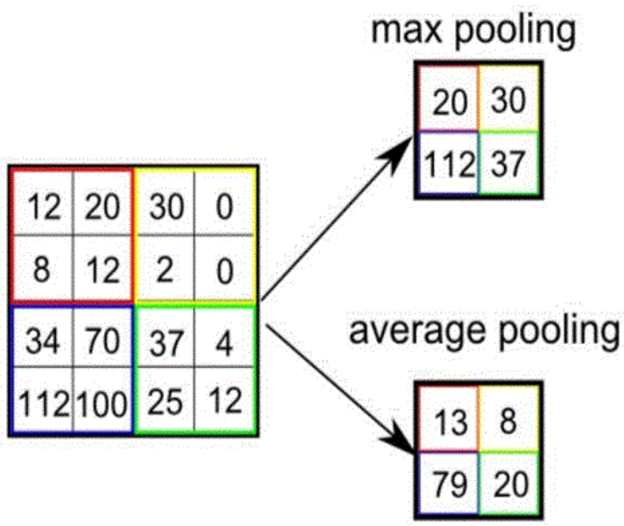



Figure 2.3: pooling layers [7]

3. **fully connected layer:**

   As we saw previously in Figure 2.4 that the fully connected layer is the final layer which is feeded to the neural network. Generally matric is flattened before getting passed on to the neurons. It is hard to follow data after this point due to presence of lot of hidden layer with variable weight for output of each neuron. All the reasoning and computation on data is done here[26]

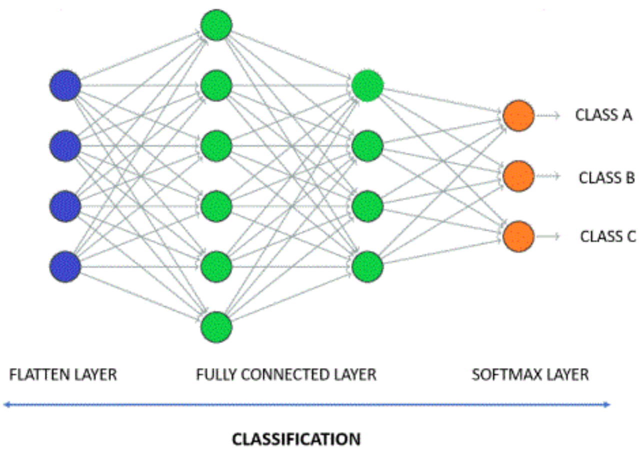



Figure 2.4: Fully Connected layers [8]

## 2.3 Application of CNN:

CNN is used for computer vision tasks, which solve image processing and ML-based problems, such as object identification, image recognition, image classification, image segmentation, and so on . However, for training, CNN requires a huge amount of data. CNN has mostly demonstrated remarkable success in traffic sign identification, medical picture segmentation, face detection, and object identification in natural photos, where there is sufficient labeled data available for training. Figure 4. Shows various CNN applications[9].

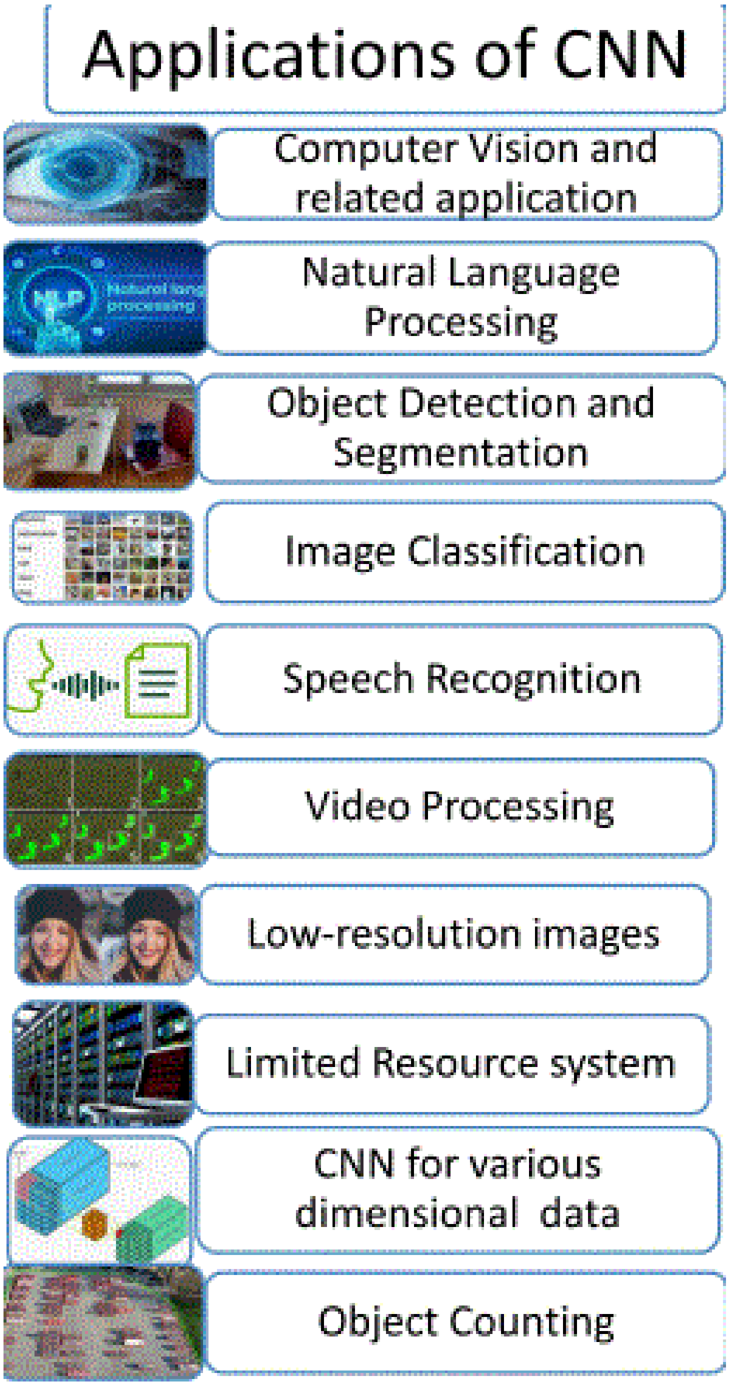



Figure 2.5: Application of CNN [9]

## 2.4 CNN Types:

There are many types of CNN, including: • LeNet (in 1998)

- AlexNet(in 2012)
- VGGNet(in 2014)
- ResNet(in2015)
- DCGAN(in 2016)
- MobileNet(in 2017)
- ShuffleNet(in 2018)
- GhostNet(in 2020)

In this article we focus on these types: VGGNet (VGG-16), ResNet, and MobileNet. We chose this models for this reasons:

 We chose VGG-16 because it is one of the most image classification models at the moment. Article published by IEEE under the title "Modality Specific CBAM-VGGNet Model for the Classification of Breast Histopathology Images via Transfer Learning" [27] published on 14 February 2023 that classify Breast Histopathology Images using VGG Net.

 We chose Res net because it is also one of the most image classification models at the moment. Article published by IEEE under the title"Self-Supervised Learning with a Dual-Branch ResNet for Hyperspectral Image Classification" [28] published on June 9, 2022, in which the author used the ResNet model for Hyperspectral Image Classification.

 We chose Mobile Net because it is the first model specifically for mobile, and it is also good at classifying images, It is still used today ,like" Mobile Net-Based Model for Histopathological Breast Cancer Image Classification"[29] published on 25 May 2023.

### 2.4.1 Proposed CNN

we proposed here a convilution neural network which has 3 convolutional layer and 3 max pooling , with activation relu function .

```
KerasModel = keras.models.Sequential([
        keras.layers.Conv2D(16,kernel_size=(3,3),activation='relu',input_shape=(s,s,3)),
        keras.layers.BatchNormalization(),
        keras.layers.MaxPool2D(2,2),
        keras.layers.Conv2D(64,kernel_size=(3,3),activation='relu'),
        keras.layers.BatchNormalization(),
        keras.layers.MaxPool2D(2,2),
        keras.layers.Conv2D(32,kernel_size=(3,3),activation='relu'),
        keras.layers.MaxPool2D(2,2),
        keras.layers.BatchNormalization(),
        keras.layers.Flatten() ,
        keras.layers.Dense(250,activation='relu') ,
        keras.layers.Dropout(rate=0.5) ,
        keras.layers.Dense(32,activation='relu') ,
        keras.layers.Dropout(rate=0.5) ,
        keras.layers.Dropout(rate=0.5) ,
        keras.layers.Dense(5,activation='softmax') ,
        ])
```

Figure 2.6: Proposed CNN

### 2.4.2 VGG Net

1. **Background:**

   **ImageNet Large Scale Visual Recognition Challenge** (ILSVRC) is an annual computer vision competition. Each year, teams compete on two tasks. The first is to detect objects within an image coming from 200 classes, which is called object localization. The second is to classify images, each labeled with one of 1000 categories, which is called image classification. VGG 16 was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014 in the paper "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION". This model won 1st and 2nd place in the above categories in the 2014 ILSVRC challenge.

2. **What is VGG:**

   VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The "deep" refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG architecture is the basis of ground-breaking object recognition models. Moreover, it is now still one of the most popular image recognition architectures [30]

3. **VGG-16:** VGG16 is a type of VGGNet that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16 weight layers [31].

4. **VGG16 Architecture:** The architecture of VGG-16 is shown in Figure 2.7; it uses 13 convolutional layers and 3 fully connected layers.

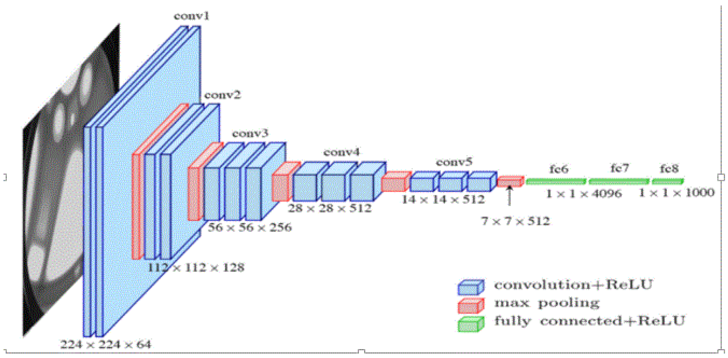



Figure 2.7: VGG-16 architecture [10]

### 2.4.3 ResNet:

1. **What is ResNet?** Residual Network (ResNet) is one of the famous deep learning models that was introduced by Shaoqing Ren, Kaiming He, Jian Sun, and Xiangyu Zhang in their

paper. The paper was named “Deep Residual Learning for Image Recognition” [32] in 2015. The ResNet model is one of the popular and most successful deep learning models so far [33]

ResNet come to solve the famous problem in neural network which is “Vanishing Gradient”. ”As more layers using certain activation functions are added to neural networks, the gradients of the loss function approaches zero, making the network hard to train”.[34]

To understand how Residual Network work let’s analyze his architecture.

2. **Architecture of ResNet:**

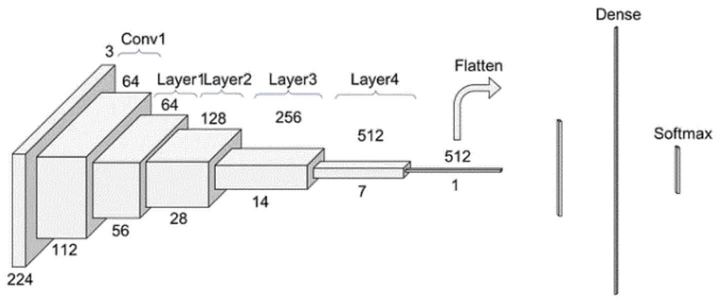



Figure 2.8: ResNet Architecture [11]

As we see in the figure 2.8 there are two essential parts in Res Net architecture which is conv1 and layers (1, 2, 3,4)

(a) **Convolution 1 :** The first step on the ResNet is a block called here Conv1 consisting on a convolution + batch normalization + max pooling operation [11]. Batch-Normalization (BN) is an algorithmic method which makes the training of Deep Neural Networks (DNN) faster and more stable [35].

(b) **ResNet Layers:** Every layer of a ResNet is composed of several blocks, the input volume is the last output volume from Conv1 [11].

(c) **What is ResNet Blocks?** A residual block is a stack of layers set in such a way that the output of a layer is taken and added to another layer deeper in the block. The non-linearity is then applied after adding it together with the output of the corresponding layer in the main path. This by-pass connection is known as the shortcut or the skip-connection. There are two main types of blocks used in ResNet, depending mainly on whether the input/output dimensions are same or different [36].

i. The identity block: Same as the one we saw in fig. The identity block is the standard block used in ResNet and corresponds to the case where the input activation has the same dimension as the output activation [37].

ii. The convolution block: We can use this type of block when the input and output dimension don’t match up. The difference with the identity block is that there is CONV2D layer in the shortcut path[37].

**A summary of what we mentioned earlier about ResNet:**

• Very deep neural networks (plain networks) are not practical to implement as they are hard to train due to vanishing gradients.

• The skip-connections help to address the Vanishing Gradient problem.

• There are two main types of ResNets blocks: The identity block and the convolutional block.

• Very deep Residual Networks are built by stacking these blocks together [37].

### 2.4.4 MobileNet:

1. **What is MobileNet?** Is a type of convolutional neural network designed for mobile and embedded vision applications. They are based on a streamlined architecture that uses depth-wise separable convolutions to build lightweight deep neural networks that can have low latency for mobile and embedded devices [38] . The original version of MobileNet (MobileNetV1) was introduced in 2017 by Google, followed by MobileNetV2 in 2018 and MobileNetV3 in 2019 [39].

2. **What is MobileNet?[36]** In MobileNet the convolution is replaced by a depth-wise separable convolution, depth-wise separable convolution is done in 2 steps:

    Depth-wise convolution

    Point-wise convolution

   The term separable is linked to the independence between these two stages.

   **o Depth-wise convolution:**

   Depth-wise convolution consists of applying a filter to each channel, unlike classic applies a filter to all channels. This difference is shown in Figure 2.9 part (a).

   **o Point-wise convolution:**

   The point-wise convolution consists of combining the outputs of the depth-wise convolution, it is also called 1x1 convolution.

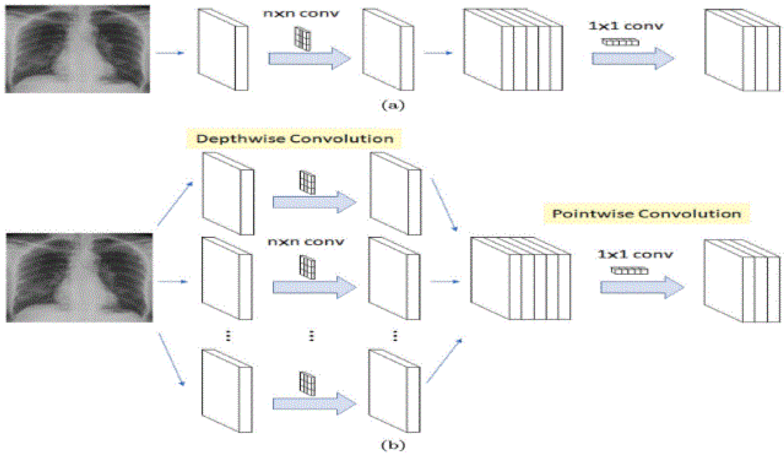



Figure 2.9: (a) Standard CNN. (b) Depthwise Separable CNN [12]

3. **MobileNet architecture:** Figure 2.10 (a) shows the detail of the MobileNet that includes convolutional, depthwise separable convolutions (DS), average pooling, fully connected (FC), and softmax layers. Figure 2.10 (b) shows an in-depth explanation of the DS layer consisting of depthwise convolution, batch normalization (BN), and rectified linear unit (ReLU), respectively.

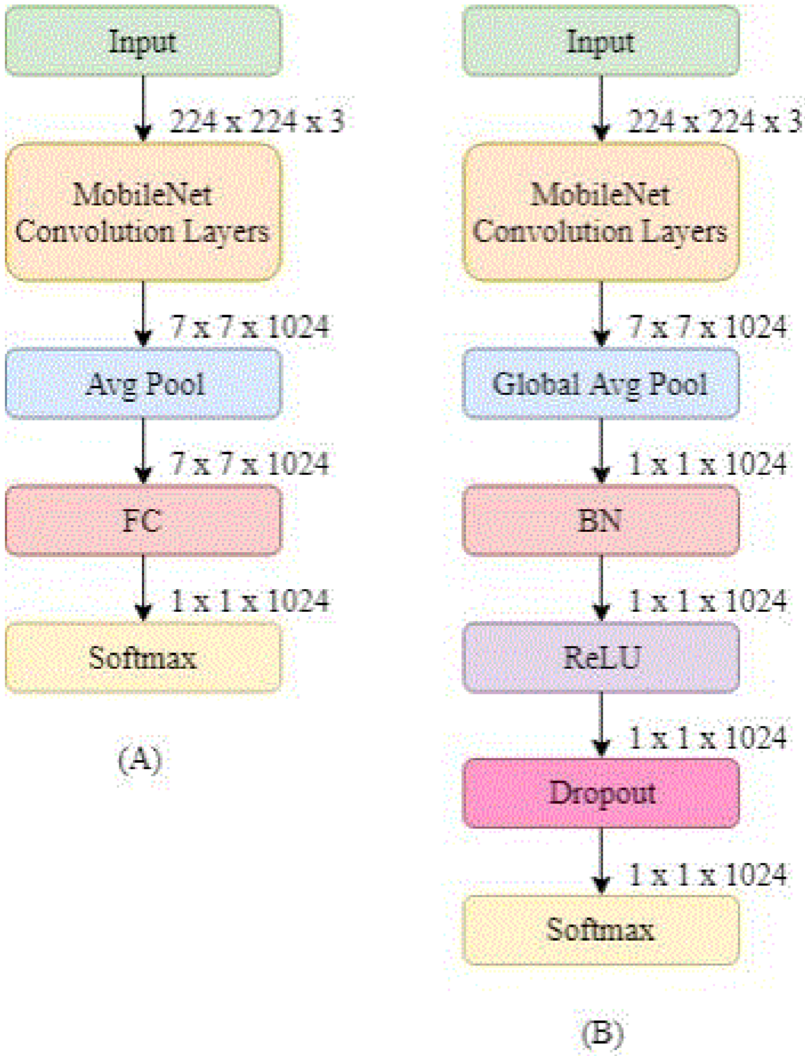



Figure 2.10: Illustration of the MobileNet architecture. (A)The overall MobileNet architecture and (B) an in-depth explanation of the DS layer [13]

**Conclusion:**

In this chapter, we have discussed about the CNN model and its type (VGG16, ResNet and Mobilenet), and this information will be the key to the third chapter, in which we will talk in detail about our topic and answer the following questions: Why did we choose the CNN model? And what will we use it for? How will the comparison be between its types?

# Chapter 3

# Heart of the matter

**Introduction**

In this chapter, which is the last chapter, we will present all our results and conclude the best model. Before that, we will explain our research in detail and mention the methods used.

## 3.1 Context:

In our work, we compared the types of CNN models (Proposed CNN, VGG-16, ResNet and Mobile Net) and then choose the best among them in terms of accuracy value. After selecting the best, we used it in the process of classifying images for five types of soil, namely yellow soil, black soil, laterite,cinder soil, and peat soil. Finally, we studied the properties of the soil and took six basic and comprehensive properties from it (texture, porosity, color, density, temperature, and pH). Then we summarized the values of these properties for each of the five soil types and organized them into five tables.

## 3.2 What is Soil?

Soil is defined as the unconsolidated mineral or organic material on the immediate surface of the Earth that serves as a natural medium for the growth of land plants (SSSA 2008). Soil is a living ecosystem full of Living organisms, with physical qualities and chemical interactions that play important roles in defining its health and quality. Soil formation is a result of the interactions of soil-forming factors, which are parent materials, climate, biological activities (biota), topography, and time. Soils of different characteristics are formed in different places, and they often reflect the degree to which these soil-forming factors have interacted [40]

## 3.3 Type of soils:

There are several types of soil, some of which are specific for building, such as gravel, and what is specific for agriculture, such as black soil, and others that are suitable for both cultivation and construction, such as sand. In this Esp(end of studies' project), we focused our attention on five types of soils: black soil, yellow soil, laterite soil , peat soil and cinder soil, hoping that in the future we will expand our study to include more number of soil types. Figures 3.1, 3.2,3.3,3.4,3.5 shows the five types of soil.

Figure 3.1: Laterite Soil

Figure 3.2: Cinder Soil

Figure 3.3: Black Soil

Figure 3.4: Yellow Soil

Figure 3.5: Peat Soil

## 3.4 Soil features:

There are several characteristics of soil, some of which are primary and some are secondary. The importance of these properties lies in distinguishing each soil from another. In this research, we wanted to study six important soil properties: texture, porosity, color, density, temperature, ph.

1. **Texture:** Soil texture refers to the proportion of sand, silt, and clay in a soil. Texture influences almost every aspect of soil use, both in agricultural and engineering applications, and even how natural ecosystems function. Many scientists consider soil texture the most important soil property as it can influence soil/water relationships, gas exchange, and plant nutrition. Accurately determining soil texture in a lab requires time and money; therefore, it is often necessary to estimate soil texture in the field by feel, which can be very accurate if done correctly[41].

2. **Porosity:** Porosity is the percentage of the soil volume occupied by pore spaces. The types of pores present in a soil are as important as the amount of pore space. Pore spaces are filled with air or water. Pore space is divided into different categories by pore diameter, especially the large soil pores that are associated with the transfer and movement of both water and air[42].

3. **Density:** The particle density refers to the mass of a unit volume of solid soil particles. No account is taken for the pore space between the particles [42] The following Table **??** shows the properties of black , cinder , laterite,yellow and peat soils:

| | Back soil | Laterite soil | Cinder soil | Peat soil | Yellow soil |
|---|---|---|---|---|---|
| Texture | 36% clay, 24.5% slit 39.5% sand | Sandy clay, loam texture | Sharp texture | considered coarse when compared with clay | Varies from sand to clay and loam. |
| Porosity (%) | 22 – 24 | Typical laterite is porous and claylike | 60.79 | 90 | hight porosity |
| Density (Mgm $\sim$ 3) | 1.55 | 1883 | 1.45 | 1.30 – 1.40 | Low density |
| Color | Black | Red | Red | Brown | yellow |
| Temperature ($c^{\circ}$) | 23 – 24 | 25 | 8 | 24 – 27 | 4 – 8 |
| PH | 6.5 – 7.5 | 7.6 | 7.5 – 8.28 | 3 – 4 | 4 – 8 |

Table 3.1: Properties of the 5 soils

The values in the Table 3.1 are excerpted from :

Black soil : texture [43] porosity [44] density [45] temperature [46] ph [47]

Cinder soil : texture [48] porosity [49] density [50] color [51] temperature [52] ph [53]

Laterite soil : texture [54] porosity [55] density [56] color [57] temperature [58] ph [59]
peat soil : texture [60] porosity [61] density [62] color [63] temperature [64] ph [65]
Yellow soil : texture [66] porosity [67] density [68] temperature [69] ph [70]

## 3.5 Related Works:

There are articles concerned with soil classification, such as what was explained by "Srivastava Pallavi" in his article" A comprehensive review on soil classification using deep learning and computer vision techniques [71] ", but like other articles, maps were used as input, in contrast to our project, which we used with pictures. . . Data entry for several reasons, the most important of which is the future outlook for our research, as we hope to develop it into a national and global site, so why not, and for this purpose, dealing with images will be easier than dealing with maps. . For example, if you are a farmer, ranch owner, or even someone who loves to explore and you want to know the type and characteristics of your soil, just take a picture of it and our program will take care of the rest.

In addition to using the images as a kind of metaphor for other articles, we wanted to get a mix and compare of the types of CNNs (which we chose to be the classification model for several reasons we mention later) and apply the best among them in one search. In this chapter we will go step by step explaining everything we did.

There are several articles interested in soil classification, some of which classify construction soils, some of which classify agricultural soils, some of which use images as input, and some that use maps. The research closest to our work among all the articles concerned with soil classification, is close in that it classifies soils and compares two deep learning models (CNN , SVM,BPNN… ) and finds that the best in terms of accuracy is the CNN model. Our research started from this point. We concluded that CNN is the best. However, the CNN model has several types, as we mentioned earlier. Which one is better? This is what our research will answer. Which one is better in classifying soil?

Therefore, we compared four types of CNN and concluded the best among them and used it to create our site, which we hope to develop into a national and international site, why not? We wanted to use images as input data because it is easy to deal with other data such as maps, for example. If you are a farmer, farm owner, or even someone who likes to explore and want to know the type of your soil and its characteristics, just take a picture of it and our program will take care of the rest.

## 3.6 Methods:

We mentioned earlier that we chose the CNN model because it is considered the best among the models in image classification, and we wanted to know exactly which of the CNN patterns is the best for our case, so we compared the four types: Proposed Cnn, VGG-16, ResNet, Mobile Net.

**• Dataset:**

**NB: Kaggle allows users to find datasets they want to use in building AI models, publish datasets, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges. Kaggle got its start in 2010 by offering machine learning and data science competitions as well as offering a public data and cloud-based business platform for data science and AI education."[33]**

The dataset of "kaggle" is the dataset used in soil classification, containing the five types mentioned previously, each type containing the following number of images:

Black soil ======= 38 image

Cinder soil ======= 30 image

Laterite soil ======= 30 image

Peat soil ======= 30 image

Yellow soil ======= 30 image

In total, it contains 158 images, and this is a very small number, so we had to expand the dataset, so we used **image generator()** function.

**NB: An AI image generator, also known as a generative model, is an artificial intelligence system designed to create new images based on a set of input parameters or conditions. These systems use machine learning (ML) algorithms that can learn from large datasets of images, allowing them to generate new images that are similar in style and content to the original dataset [72]**

After we used image generator () function, the number of images in each type became as follows :

Black soil ======= 1730 image

Cinder soil ======= 1264 image

Laterite soil ======= 856 image

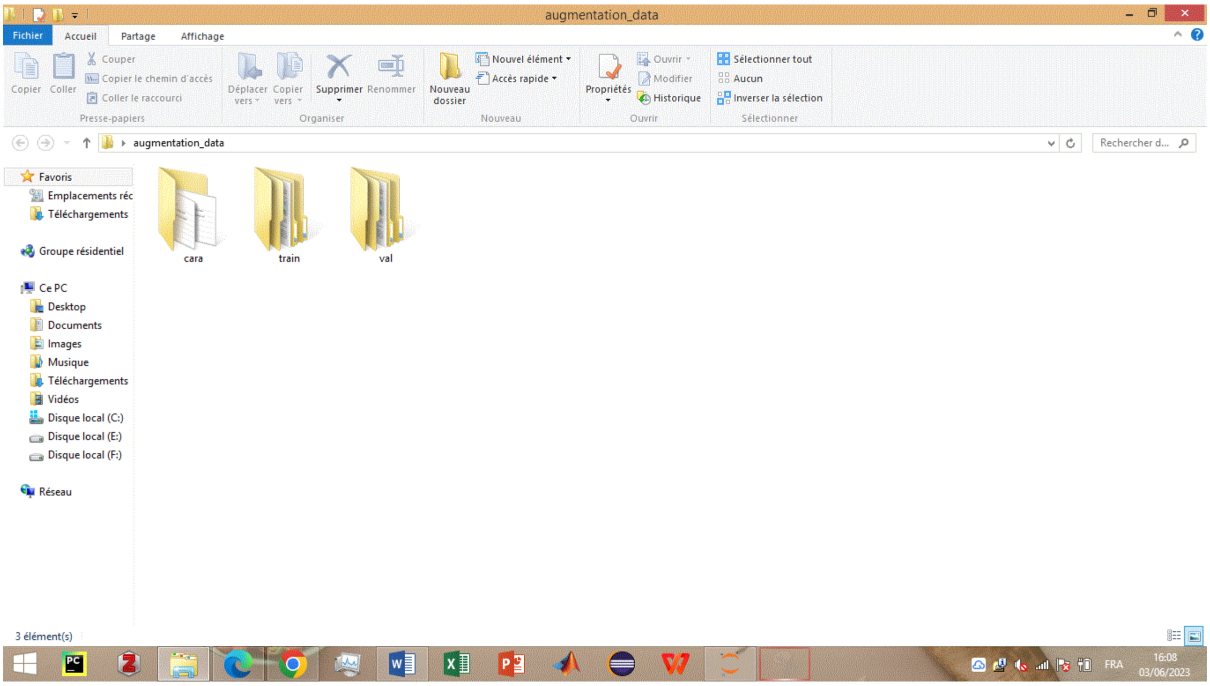
Peat soil ======= 855 image

Yellow soil ======= 856 image

In total, it contains 5561 images, After that, we divided the new database into two parts, a training section(80%) and a test section(20%), by the split-folders function, using the following code :

```
!pip install split-folders
import splitfolders
database=('C:/Users/sbi01/Desktop/Soil-Dataset_aug/')
splitfolders.ratio(database , 'C:/Users/sbi01/Desktop/augmentation_data/', seed=1254,ratio=(0.8,0.2))
```

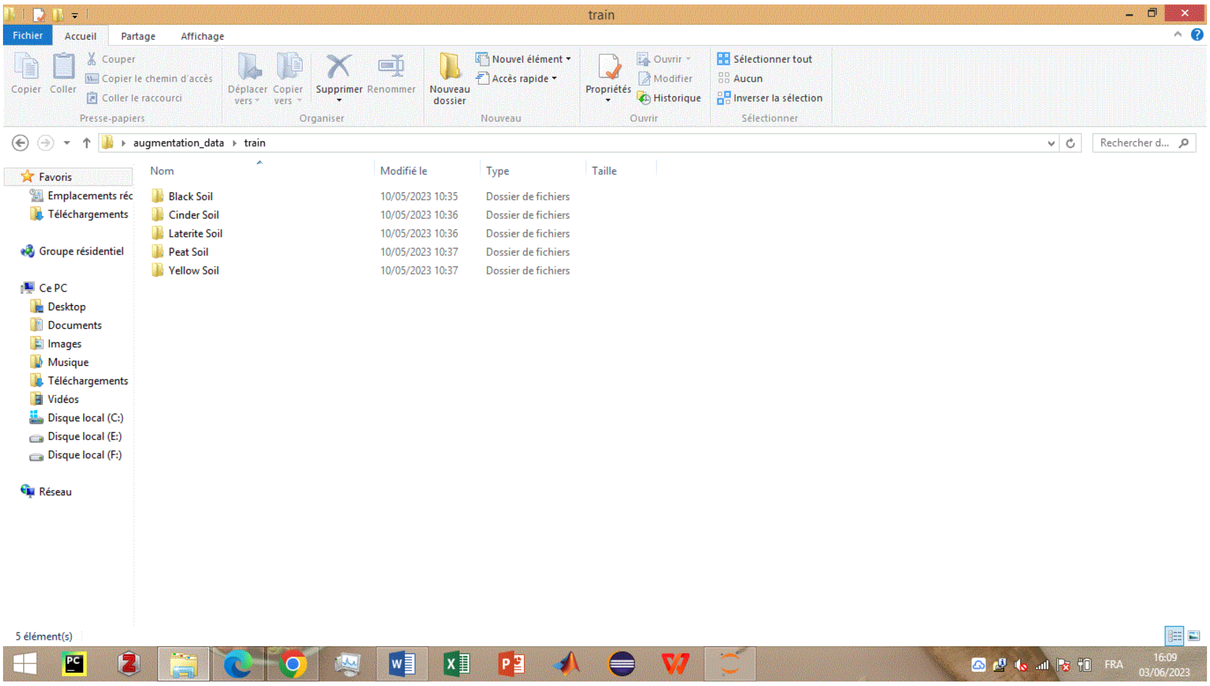
Finally, we have two sections, each section contains five types of soil train folder contain 4226 images and the test folder contain 1389 images.

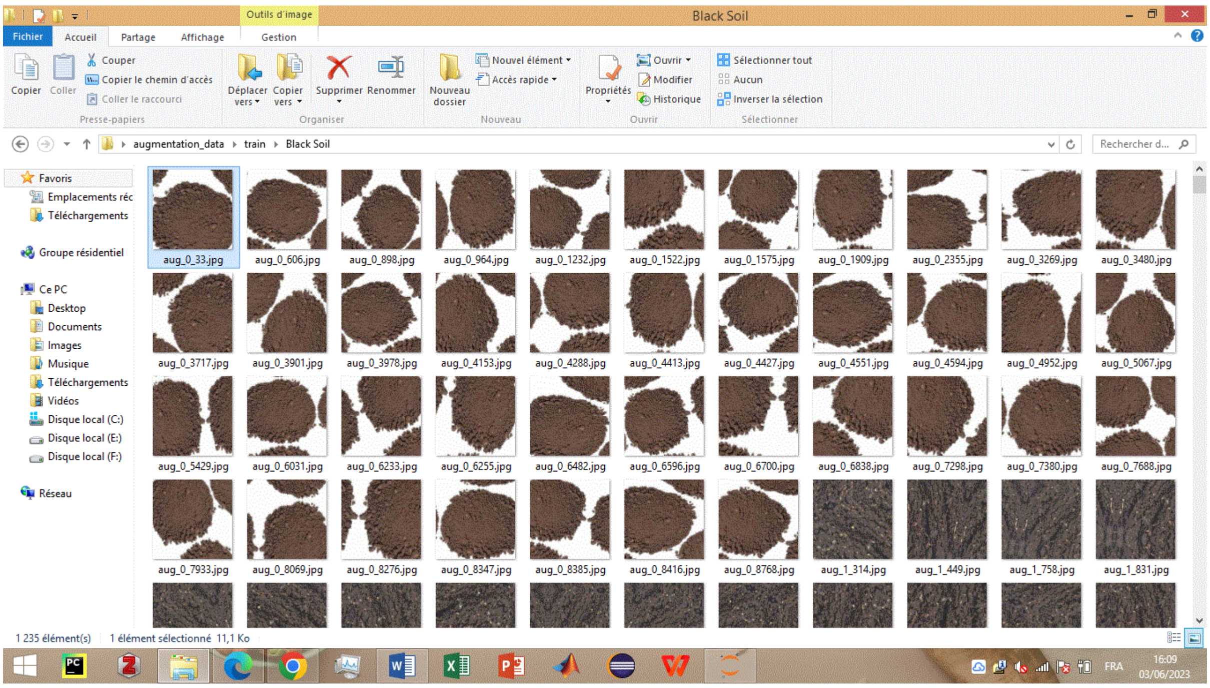



Now let's move on to the practical part:

1. First we must import the necessary libraries (We take as an example the libraries needed for the VGG-16 model):

2. Second, we load the data set from where it is located :


train
Fichier
Accueil
Partage
Affichage
augmentation_data
train
Nom
Modifié le
Type
Taille
Black Soil
Cinder Soil
Laterite Soil
Peat Soil
Yellow Soil
10/05/2023 10:35
10/05/2023 10:36
10/05/2023 10:36
10/05/2023 10:37
10/05/2023 10:37
Dossier de fichiers
5 élément(s)


Black Soil
Outils d'image
Gestion
augmentation_data
train
Black Soil
aug_0_33.jpg
aug_0_606.jpg
aug_0_898.jpg
aug_0_964.jpg
aug_0_1232.jpg
aug_0_1522.jpg
aug_0_1575.jpg
aug_0_1909.jpg
aug_0_2355.jpg
aug_0_3269.jpg
aug_0_3480.jpg
aug_0_3717.jpg
aug_0_3901.jpg
aug_0_3978.jpg
aug_0_4153.jpg
aug_0_4288.jpg
aug_0_4413.jpg
aug_0_4427.jpg
aug_0_4551.jpg
aug_0_4594.jpg
aug_0_4952.jpg
aug_0_5067.jpg
aug_0_5429.jpg
aug_0_6031.jpg
aug_0_6233.jpg
aug_0_6255.jpg
aug_0_6482.jpg
aug_0_6596.jpg
aug_0_6700.jpg
aug_0_6838.jpg
aug_0_7298.jpg
aug_0_7380.jpg
aug_0_7688.jpg
aug_0_7933.jpg
aug_0_8069.jpg
aug_0_8276.jpg
aug_0_8347.jpg
aug_0_8385.jpg
aug_0_8416.jpg
aug_0_8768.jpg
aug_1_314.jpg
aug_1_449.jpg
aug_1_758.jpg
aug_1_831.jpg
1 235 élément(s)
1 élément sélectionné 11,1 Ko

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="whitegrid")
import os
import cv2
import tensorflow as tf
import keras
```

```python
from keras.layers import Input, Lambda, Dense, Flatten
from keras.models import Model
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
import glob as gb
```

3. Thirdly, we process the images, and this process includes resizing the images and divide the train set to images(Xtrain) and labels(ytrain) :

```

trainpath = 'C:/Users/sbi01/Desktop/augmentation_data/'
testpath = 'C:/Users/sbi01/Desktop/augmentation_data/'
carapath= 'C:/Users/sbi01/Desktop/augmentation_data/'
```

```
for folder in  os.listdir(trainpath + 'train') :
    files = gb.glob(pathname= str( trainpath +'train//' + folder + '/*.jpg'))
    print(f'For training data , found {len(files)} in folder {folder}')
```

```
For training data , found 1235 in folder Black Soil
For training data , found 928 in folder Cinder Soil
For training data , found 688 in folder Laterite Soil
For training data , found 687 in folder Peat Soil
For training data , found 688 in folder Yellow Soil
```

```
for folder in  os.listdir(testpath  + 'val') :
    files = gb.glob(pathname= str( testpath  +'val//' + folder + '/*.jpg'))
    print(f'For test data , found {len(files)} in folder {folder}')
```

```
For test data , found 495 in folder Black Soil
For test data , found 336 in folder Cinder Soil
For test data , found 186 in folder Laterite Soil
For test data , found 186 in folder Peat Soil
For test data , found 186 in folder Yellow Soil
```

4. Fourthly , we define the model(We take as an example Proposed cnn) :

```
X_train = []
y_train = []
for folder in  os.listdir(trainpath +'train') :
    files = gb.glob(pathname= str( trainpath +'train//' + folder + '/*.jpg'))
    for file in files:
        image = cv2.imread(file)
        image_array = cv2.resize(image , (s,s))
        X_train.append(list(image_array))
        y_train.append(code[folder])
```

```
X_test = []
y_test = []
for folder in  os.listdir(testpath +'val') :
    files = gb.glob(pathname= str(testpath + 'val//' + folder + '/*.jpg'))
    for file in files:
        image = cv2.imread(file)
        image_array = cv2.resize(image ,(s,s))
        X_test.append(list(image_array))
        y_test.append(code[folder])
```

```
X_cara = []
y_cara = []
files = gb.glob(pathname= str(carapath + 'cara/*.jpg'))
for file in files:
    image = cv2.imread(file)
    image_array = cv2.resize(image ,(2000,1500))
    X_cara.append(list(image_array))
   # y_cara.append(code[file])
```

```
KerasModel = keras.models.Sequential([
        keras.layers.Conv2D(16,kernel_size=(3,3),activation='relu',input_shape=(s,s,3)),
        keras.layers.BatchNormalization(),
        keras.layers.MaxPool2D(2,2),
        keras.layers.Conv2D(64,kernel_size=(3,3),activation='relu'),
        keras.layers.BatchNormalization(),
        keras.layers.MaxPool2D(2,2),
        keras.layers.Conv2D(32,kernel_size=(3,3),activation='relu'),
        keras.layers.MaxPool2D(2,2),
        keras.layers.BatchNormalization(),
        keras.layers.Flatten() ,
        keras.layers.Dense(250,activation='relu') ,
        keras.layers.Dropout(rate=0.5) ,
        keras.layers.Dense(32,activation='relu') ,
        keras.layers.Dropout(rate=0.5) ,
        keras.layers.Dense(5,activation='softmax') ,
        ])
```

5. Fifthly, we compile the model(We take as an example Mobile Net model):

```
model_truck.compile(optimizer='Adam', loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True), metrics=['acc'])
```

6. Finally, we fit the model(We take as an example ResNet model):

## 3.7 Results:

The results obtained through this work are organized in table as follow, but before the results we will make some definitions:

• Accuracy: AI accuracy is the percentage of correct classifications that a trained machine learning model achieves, i.e., the number of correct predictions divided by the total number of predictions across all classes. It is often abbreviated as ACC [33]

• Loss: Loss is a value that represents the summation of errors in our model. It measures how well (or bad) our model is doing. If the errors are high, the loss will be high, which means

```
history = model_truck.fit(training_image_data, epochs =20,
                          validation_data=validation_image_data)

Epoch 1/20
133/133 [==============================] - 624s 5s/step - loss: 0.9532 - acc: 0.6391 - val_loss: 0.7516 - val_acc: 0.6782
Epoch 2/20
```

that the model does not do a good job. Otherwise, the lower it is, the better our model works [73]

- Time$_t$ : $trainingtime.$
- S$_img : Thesizeoftheimageweentered \quad EpT : totaleposhesthatweuseit.$
- EpS: The number of eposhe in which we obtained the highest accuracy

| | VGG-16 | ResNet | Mobile Net | Proposed CNN |
|---|---|---|---|---|
| ACC | 82% | 79% | 77% | 86% |
| LOSS | 0.66 | 1.14 | 0.79 | 0.55 |
| Timet | 7 h&48 min | 21 min&21 s | 8 h&40 min | 4 min&33 s |
| S img | 32 | 32 | 224 | 32 |
| EpT | 10 | 100 | 100 | 100 |
| EpS | 10 | 11 | 65 | 4 |

Table 3.2: Table showing the resaults after trainig the 4 models

Now let's start analyzing these results:

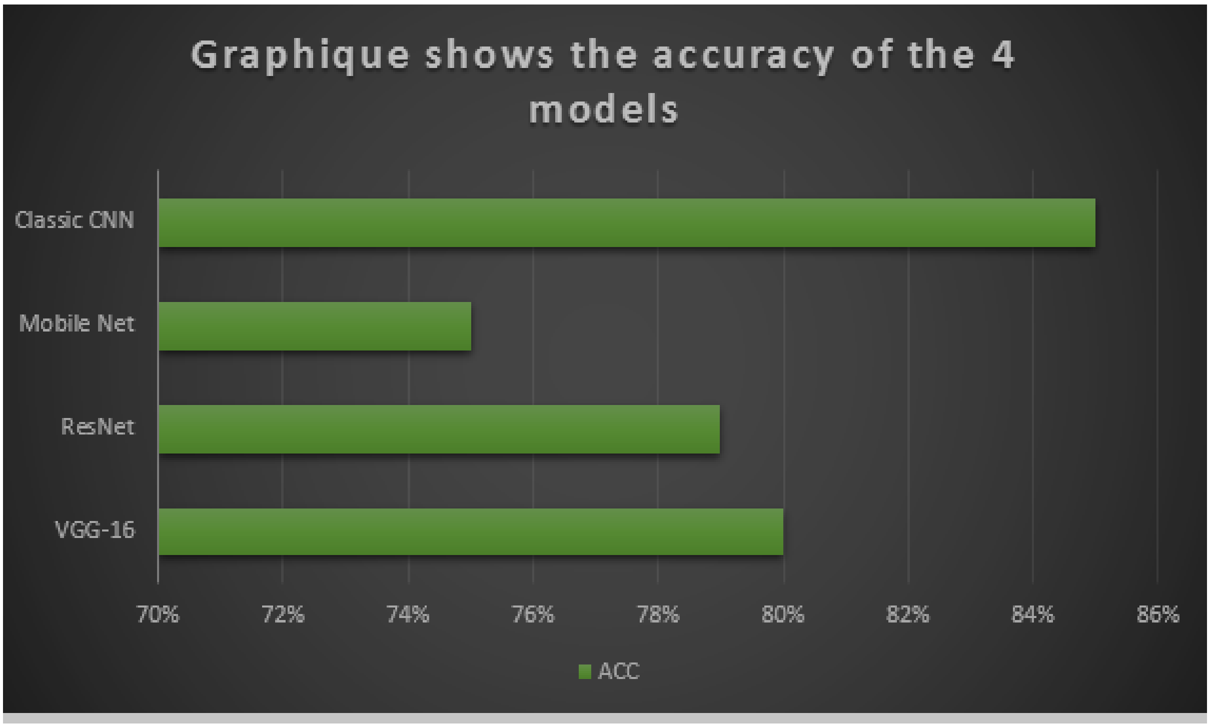
• As we note, and as it is known, the first unchallenged in terms of accuracy(86%) and time spent(3min) is Proposed CNN.

• We note in VGG-16 that it is the best after Proposed CNN in terms of accuracy(80%), and the least in terms of errors(loss) (0.66), but on the other hand, It takes a lot of time in implementation (7h.48min) in only 10 eposhes(this is not new to the VGG model because the original VGG model was trained on the Nvidia Titan GPU for 2–3 weeks) As an evaluation, it is very good, despite the large time it took.

• ResNet achieved an estimated accuracy rate of (79%) and an estimated error (loss) rate of 1.35 in a time of (4 min 24 s). In general, it is a good model, but not the best.

• Mobile Net is the least among all models in terms of accuracy (76%) and an estimated error (loss) rate of 0.79, in addition to that it takes a long time (8 h 40min) and this is because it is considered among the pre-trained models pre-trained that's learned on large-scale datasets.

• When we talk about eposhes we nota that the most is Standard CNN and the worst is Mobile Net because the input image size of mobile net is 96 while the input image size of auther model is 32 (because the mobile net accept the image size 96 , 160)



Let's see pictures of the results of some pictures after testing them on the four models: • This image show result of classification an black soil image using Proposed CNN:

```
1/1 [==============================] - 2s 2s/step
This Soil is a : Black Soil
```

And this is the features of the black soil:

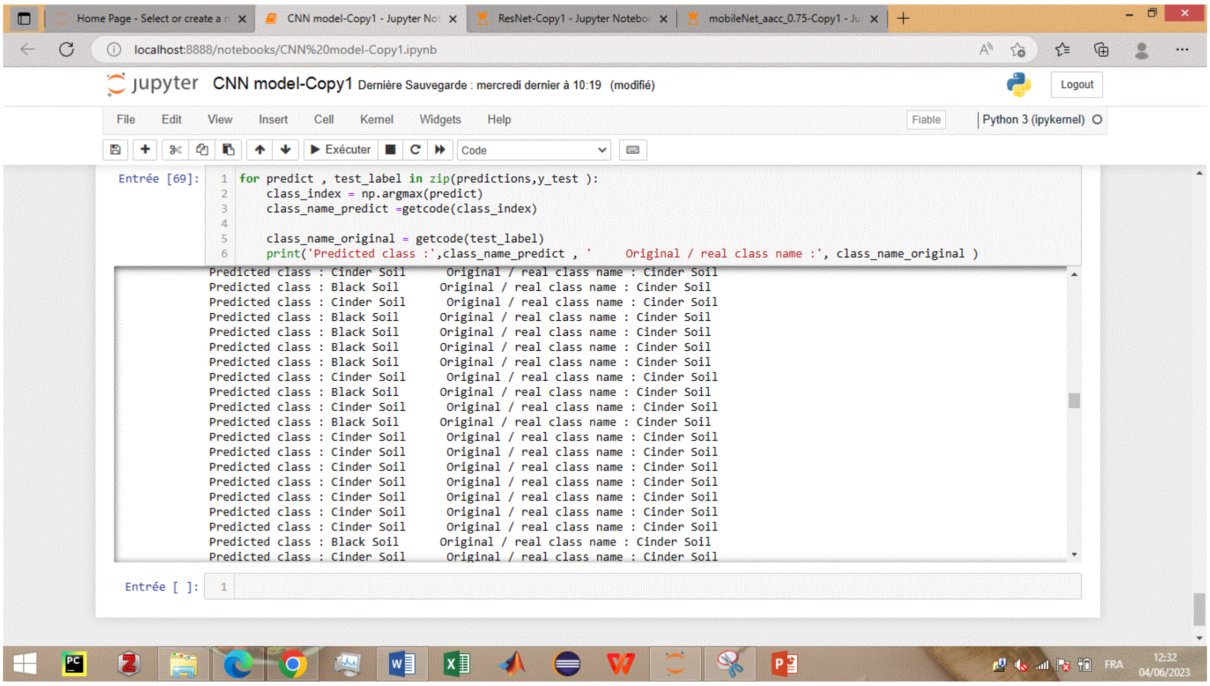
```
The features of  Black Soil is:

]: (-0.5, 1999.5, 1499.5, -0.5)
```

### Black soil

| | |
|---|---|
| Texture | 36% clay , 24.5%slit , 39.5 sand |
| Porosity(%) | 22-24 |
| Density(Mg m^3) | 180 |
| Color | black |
| Temperature(C°) | 21-27 |
| Ph | 7.2-8.5 |

• This is a list showing the original labels of test images and the predict name that the model got it, if there are the same that mean the model worked fine else the opposite is true.



**Conclusion:**

After we noticed the previous results and analyzed them, we conclude that the best model after Proposed CNN is ResNet, although VGG is more accurate than ResNet, but because we are in the era of speed, and if the model takes a long time, even if its accuracy is high, many people will not use it. As for Mobile Net, it may work well when the data set is large(contains millions of images).

# Conclusion

After we first trained 4 types of CNN models, Standard Cnn, Res Net, VGG-16 and Mobile Net and then tested them on a test dataset containing 1389 images, we got the highest accuracy rate of 86% in Proposed Cnn, followed by VGG of 80%, then ResNet 79%, and finally Mobile Net 76%. In the latter we adopted the Proposed Cnn because it was the best in terms of accuracy and time. It took 4 minutes and 33 seconds in 4 Eposhes, that's mean one minute and eight seconds per eposhe. It has been adopted as a future plan to design and develop a website with national and international specifications for classifying soils of all kinds, in addition to expanding and reviewing the list of characteristics through conducting local experiments and adding arable products in each soil.

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