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Agricultural soil characterization and crop recommendation using deep learning algorithms: Model Selection and AI Application Development

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Dedication

I dedicate this work to:

My beloved mother

My dear father

And my beloved sisters and brothers

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Agricultural soil characterization and crop recommendation using deep learning algorithms: Model Selection and AI Application Development

Abstract

Agriculture is vital, and soil is a fundamental component with unique characteristics for different crops. This thesis research aimed to develop a deep learning-based system for soil type classification. It explores the performances of eight CNNs architectures namely, DenseNet201, MobileNetV3Large, VGG16, VGG19, InceptionV3, ResNet50, Xception, and a novel architecture referred to as simple_architecture, for accurately classifying agricultural soil types found in Maradi, Niger. The research methodology encompasses data collection, cleaning, preprocessing, model building, hyperparameter optimization, model compilation, and the development of an AI-based application. The findings highlight that ResNet50 and DenseNet201 were better than other models for all performance metrics. Thus, the developed application is meant to empower farmers to optimize their practices in the face of land degradation and climate change challenges.

Keywords: soil classification; deep learning; convolutional neural networks; transfer learning; Climate change; AI.

Résumé

L'agriculture est vitale et le sol est un élément fondamental présentant des caractéristiques uniques pour différentes cultures. Cette recherche vise à developper un system de classification de type de sol basé sur le deep learning. Elle explore les performances de huit architectures de CNN à savoir, DenseNet201, MobileNetV3Large, VGG16, VGG19, InceptionV3, ResNet50, Xception, et simple_architecture, pour classer les types de sol agricoles indentifiés à Maradi, Niger. La méthodologie de recherche comprend la collecte de données, le nettoyage, le prétraitement, le developpement de modèles, l'optimisation des hyperparamètres, la compilation de modèles et le développement d'une application basée sur l'IA. Les résultats montrent que ResNet50 et DenseNet201 sont plus performants que les autres modèles. Ainsi, l'application est destinée à aider les agriculteurs à faire face à la dégradation des sols et du changement climatique.

Mots-clés: classification des sols; Deep learning; Réseaux Neuronaux Convolutifs; transfer learning; Changements climatiques; IA.

Acronyms and abbreviations

ANN: Artificial Neural Network

CNN: Convolutional Neural Network

CSV: Comma-separated values

DL: Deep learning

DRL: Deep Reinforcement Learning

ED-ICC: Ecole Doctorale Informatique et Changement Climatique

EMD: Empirical mode decomposition

FCNN: fully connected neural networks

FDA: Fisher Decrement Analysis

GAN: Generative Adversarial Networks

GRU: Gated Recurrent Unit

HOG: Histogram Oriented Gradient

ICC: Informatics for Climate Change

INRAN: Institut National Agronomique du Niger

JSON: JavaScript Object Notation

KPCA: Kernel PCA

LBP: Local Binary Pattern

LDA: Linear Decrement Analysis

LSTM: long short-term memory

MLP: Multilayer Perceptron

NN: Neural Networks

PCA: Principal Components Analysis

QGIS: Quantum Geographic Information System

RL: Reinforcement Learning

RMSprop: Root Mean Squared Propagation

SIFT: Scale Invariant Feature Transform

SORAZ: Société de raffinage de Zinder

SURF: Speeded Up Robust Features

SVM: Support Vector Machine

WASCAL: West African Science Service Centre on Climate Change and Adapted Land Use

WSGI: Web Server Gateway Interface

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Introduction

1. Context

Agriculture serves as the lifeblood of numerous nations, with soil playing a pivotal role as its fundamental component. Different soil varieties exist, each possessing distinct attributes that cater to the specific needs of different crops (Waikar *et al*., 2020). The role of soil detection in environmental research is significant, as it aids in identifying suitable plants for agriculture. This knowledge assists farmers in determining the types of plants that can thrive in specific soil conditions. Furthermore, soil detection can facilitate the practice of blending different plant species in particular regions or cultivating novel crop varieties on farmland. (Rahouma & Aly, 2020).

It is a prominent and pressing concern in numerous countries, capturing significant attention. The global population is rapidly increasing, resulting in a corresponding surge in food demand. Conventional farming techniques fall short of meeting these escalating requirements, compelling farmers to deplete arable soil resources. To achieve optimal crop yields, farmers need to possess knowledge of the appropriate soil types for specific crops, given the intensified food demand. While there exist various laboratory and field methods for soil classification, they suffer from limitations such as being time-consuming and labor-intensive. Hence, the need for computer-based soil classification appraches that can assist farmers in the field without consuming excessive time is evident (Srivastava *et al*., 2021).

Thus, Artificial intelligence (AI) which describes a computer's or robot's ability to do actions that are generally performed by intelligent beings (B.J, 2023), plays a critical role in improving agricultural practices by encouraging the reduction of workload for farmers production, managing pests, monitoring soil quality, the production of healthier crops, and growth conditions, organizing agricultural data, and enhancing various tasks throughout the entire food supply chain. Deep learning, a modern and sophisticated method of processing images and analyzing data, has a lot of promise and potential. Deep learning has lately entered the world of agriculture due to its demonstrated performance in a variety of disciplines (Kamilaris & Prenafeta-Boldú, 2018).

Depending on the desired outcomes, various algorithms are applied to the images. Soil classification can be achieved by considering different soil properties such as color, texture, and particle size. In the present context, soil classification can be performed through two distinct approaches: one involving handcrafted features and the other utilizing features generated by deep neural networks. (Srivastava *et al*., 2021). Machine learning has made significant contributions across diverse domains and serves as a powerful tool for data processing. However, traditional machine learning techniques often require manual feature extraction methods to analyze raw natural data, as they lack inherent capabilities in this regard. As hardware computing abilities and storage capacities have advanced, the potential of machine learning has grown. By incorporating more complex structures, machine learning can achieve deep representations of data, enhancing its capabilities and performance. (Schmidhuber, 2015). Deep learning can be conceptualized as a form of representation learning that enhances multilevel representations through the utilization of deep artificial neural networks (ANNs) comprising multiple layers of neurons, also known as nonlinear modules (Zhou *et al*., 2019).

Utilizing Deep Learning models for Image Classification offers numerous benefits. Traditional Machine Learning models heavily rely on accurately labeled data to achieve satisfactory results. In contrast, Deep Learning architectures can effectively learn without explicit labeling, thanks to the remarkable ability of Neural Networks to adapt and learn patterns autonomously. Additionally, Deep Learning consistently delivers exceptional outcomes, surpassing alternative methods, particularly in domains such as speech, language, and vision (B. *et al*., 2020). The aforementioned factors underlie the selection of the subject "Performance Comparison of Various Convolutional Neural Networks for Soil Type Classification in Maradi, Niger."

Furthermore, the performance of target learners in specific domains can be improved through transfer learning by leveraging the knowledge acquired from various sources. This approach reduces the reliance on extensive target domain data for constructing effective target learners. Due to its extensive potential applications, transfer learning has gained substantial popularity and emerged as a promising field within the realm of machine learning (Zhuang *et al*., 2020). Hence, this research investigates the capabilities of a novel CNN model, along with seven pre-trained CNN models specifically chosen based on their performance on the imagenet dataset. These models include VGG (Boesch, 2021) (B. *et al*., 2020), ResNet (Boesch, 2022), MobileNet (*Image Classification with MobileNet | Built In*, n.d.), Desnsnet (Huang *et al*., 2018) and Inception v3 (Szegedy *et al*., 2015).

2. Problem statement

in West Africa the success of farming is heavily reliant on the characteristics of the soil, as it determines the appropriate crop selection, fertilizer usage, and farming techniques. Therefore, soil analysis becomes crucial in making informed decisions about farming practices (Jones, 1993).

Particularly, Sub-Saharan Africa (SSA) has faced several challenges throughout the years, including a rapidly expanding population, significant urbanization, climate change, and persistent food insecurity(Sakho-Jimbira & Hathie, 2020). Agriculture serves as the primary source of food and income for more than 80 % of the population of Niger. The majority of people engage in cultivating crops and raising livestock on small-scale family-owned farms (*Niger | Integrated Production and Pest Management Programme in Africa | Food and Agriculture Organization of the United Nations*, 2023). Given the fact that the importance of soils in supplying the rising worldwide demand for food and feed cannot be overstated (Silver et al., 2021) and the traditional method of soil analysis involving laboratory testing is expensive and time-consuming for farmers in the region, It is particularly a great challenge to sustainable farming in Niger where every year, about 100,000 hectares of arable land are getting lost due to water erosion thus creating a pressing need to develop a more accessible and efficient solution to assist farmers in making appropriate soil-related decisions to address the problem (United Nations Convention to Combat Desertification, 2018).

Part of the solution is for farmers to know they type of soil and therefore identify the most suitable crops and fertilizers to unpack the potential of the soil. Thus, in the present era, the advancement of agricultural technologies and the adoption of digitalized agricultural practices have resulted in enhanced productivity and improved quality in the field of agriculture. Alongside the progress in agricultural technologies, smart agriculture significantly contributes to the global economy(Aydinbaş, 2023). However, Artificial Intelligence could help empower farmers to be more resilient to the problems of land degradation and adverse effects of climate change. It can actually allow the development of an application which would enable them to accurately identify their soil type, comprehend its characteristics, and receive personalized recommendations for crops, fertilizers, irrigation systems, and farming techniques for a sustainable farming system (Sachithra & Subhashini, 2023).

By implementing such an application, farming productivity can be significantly enhanced, while also helping to mitigate the effects of environmental degradation on crop yield. However, language barrier often poses a challenge for farmers when adopting technological tools (Nmadu *et al*., 2013). Therefore, it is crucial to design the application with a user-friendly interface that is easily accessible and understandable for farmers from diverse linguistic backgrounds.

Ultimately, it comes to know how can the development of an AI-based soil identification application improve farming practices and provide farmers with a cost-effective and efficient means of analyzing their soil, making well-informed decisions, and ultimately sustainably increasing their productivity.

3. Research questions

The main question this research will answer is: What is the effectiveness of a deep learning-based system for classifying soil types in Maradi, Niger?

Specifically, the study aims to address the following questions:

- Can different deep learning models be built for soil types classification in Maradi?
- Which of the studied models is the most performant for soil type classification in Maradi?
- Can an AI-based application accurately classify soil types in Maradi?
- Can locale language be integrated into the application?

4. Research hypotheses

4.1 The main hypothesis

The main hypothesis of this work is that a deep learning-based system can accurately classify soil types in Maradi, Niger.

4.2 Specific hypothesis

- Different deep learning models can be built for soil types classification in Maradi;
- There is a significant difference in the performance of different convolutional neural networks for soil type classification in Maradi;
- An AI-based application can be built for accurately classifying soil in Maradi;
- Local language can be integrated into the application.

5 Research objectives

To accomplish this applied research, the main research objective is to build deep learning-based soil type classification system in Maradi, Niger.

To achieve the main objective, the following specific objectives must be achieved

- To build different deep learning models for soil types classification in Maradi;
- To identify out of the studied models the best Convolutional neural network architecture in classifying soil types in Maradi;
- To build an AI-based application for soil type classification in Maradi;
- To integrate local language in the system.

To achieve the above-mentioned objectives, a comprehensive literature review has been carried out as follows.

Chapter 1: literature review

1.1 History of deep learning

The origins of ANNs are in the 1940s when Warren McCulloch and Walter Pitts suggested using neural networks to simulate human brains in a 1943 study (McCulloch & Pitts, 1943). The earliest known neural network was created by Minsky and Dean Edmunds in 1951 with their stochastic neural analog reinforcement calculator (Poulton, 2001). In 1960, Henry J. Kelley is credited with being the visionary who built the continuous back propagation model's foundation. Stuart Dreyfus later created a streamlined version of the model in 1962 using only the chain rule. Although the idea of back propagation which entails propagating errors backward to help with training was known in the early 1960s, it was defined by its complexity and inefficiency, and it wasn't until 1985 that it started to show real promise. Unfulfilled promises led to the beginning of the first AI winter in the 1970s. Both deep learning (DL) and artificial intelligence (AI) research suffered from this shortage of funding. There were, however, some fortunate people who persisted in their studies despite the lack of funding. At Bell Labs, Yann LeCun successfully demonstrated the use of backpropagation, which was a huge advancement at the time. His ground-breaking research combined backpropagation and convolutional neural networks to reliably decode handwritten digits. Eventually, this ground-breaking technique was used to read the handwritten digits on checks. Convolutional neural networks can now be trained without the requirement for layer-by-layer pre-training thanks to a notable advance in GPU speeds in 2011. This improved computing power made deep learning's astounding efficiency and performance advantages clear. The development of AlexNet, a convolutional neural network design that excelled in numerous international contests between 2011 and 2012, is a noteworthy illustration of this. Dropout techniques and rectified linear units were used to increase the system's efficiency and speed (Foote, 2022).

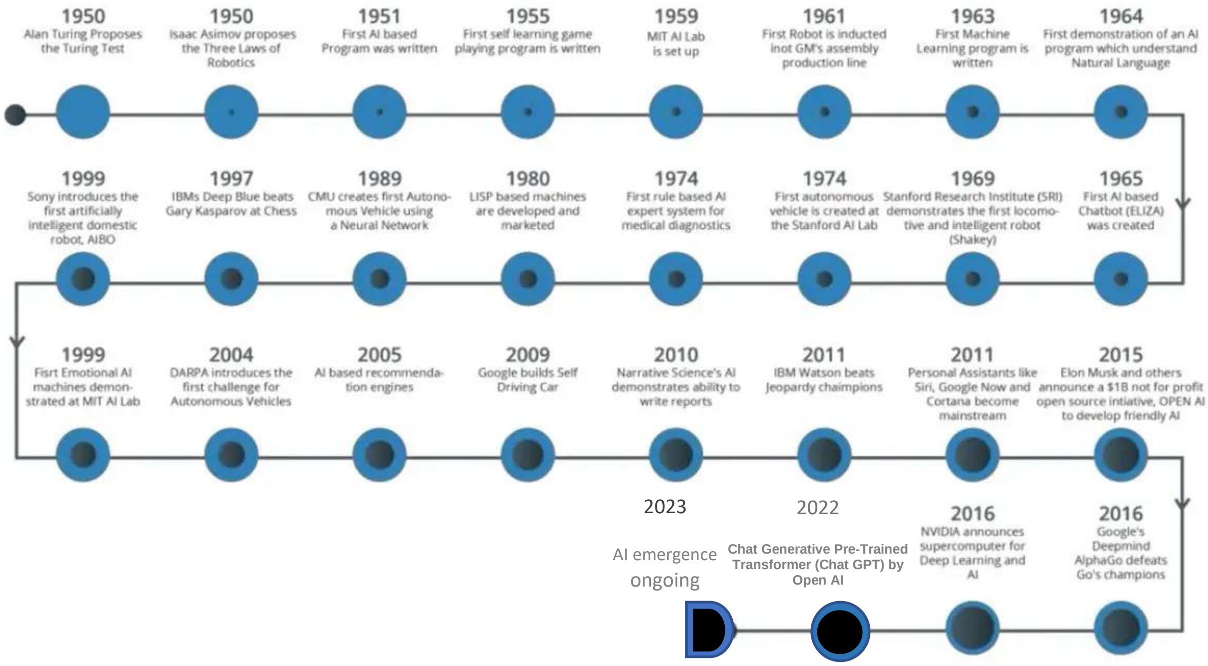

Figure 1: Deep learning milestones

Source: (*Deep Learning 101 - Part 1: History and Background*, 2017)

The provided diagram (Figure 2*)* showcases the basic block diagram of a perceptron used within neural networks.

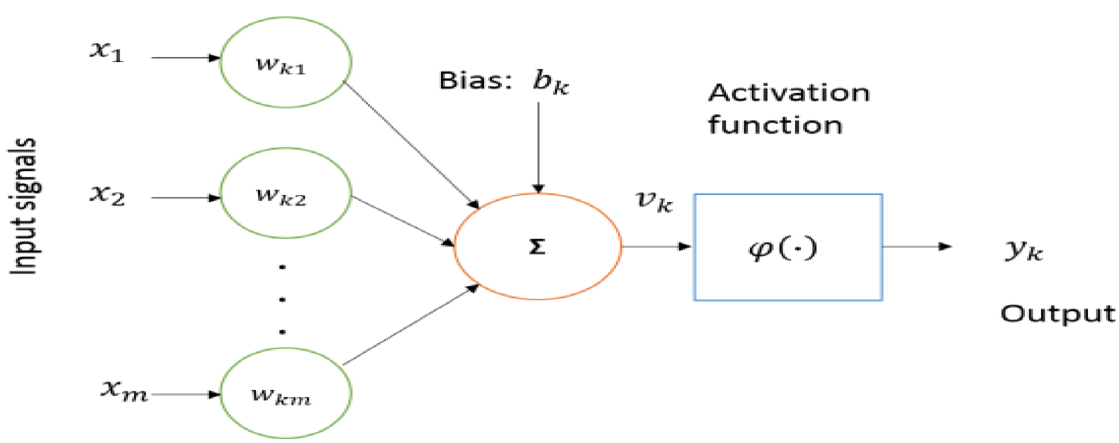

Figure 3: simple Model of a neuron

Source:(Alom *et al*., n.d.)

The diagram provided illustrates the core structure of a neuron, highlighting its non-linear characteristics. Within this model, the input signals are denoted as $x1$, $x2$, $x3$, $\cdots$ xm, while the synaptic weights are represented by $wk1$, $wk2$, $wk3$, $\cdots$ wkm. The linear combination of the input signals is denoted as Vk, and the activation function (e.g., sigmoid function) is represented by φ $(\cdot)$. The resulting output is indicated as yk. To introduce bias, the linear combiner combines the outputs vk, thereby applying an affine transformation to generate the outputs yk. The functionality of the neuron can be mathematically expressed as follows:

$$\mathcal{V}k = \sum_{j=1}^{m} = w_{kj}x_j \quad (1)$$

$$\mathcal{Y}_k = \varphi(\mathcal{V}_k + b_k) \quad (2)$$

Artificial Neural Networks (ANNs) are comprised of Multilayer Perceptrons (MLPs) which are constructed with one or more hidden layers encompassing numerous hidden units or neurons..

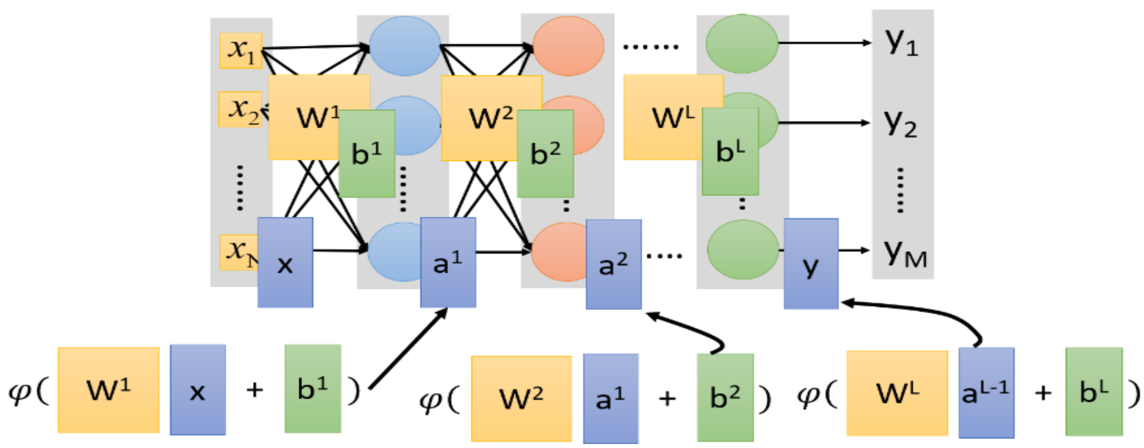

Figure 4: Multiple layers of the perceptron of Neural Network

Source:(Alom *et al*., n.d.)

1.2 Types of DL Approaches

Deep learning methods can be classified into different categories, such as supervised learning, semi-supervised learning (also referred to as partially supervised learning), unsupervised learning, and self-supervised learning. Additionally, there is a distinct category known as Reinforcement

Learning (RL) or Deep RL (DRL), which is occasionally linked to semi-supervised learning or even considered as part of unsupervised learning approaches (Alom *et al.*, n.d.; Ozsoy *et al.*, 2022).

1.2.1 Supervised Learning

It is the process of training a model using labeled data, and it encompasses two primary forms of learning: classification and regression. Regression is employed when the desired output is continuous, while classification is used when the desired output falls into specific categories (Dridi, 2022). In supervised learning, there exists an environment characterized by a set of inputs and their corresponding outputs, denoted as $(xt, yt) \sim \rho$. For instance, when the intelligent agent predicts $\hat{y}t = f(xt)$ given an input xt, it receives a loss value $l(yt, \hat{y}t)$. Subsequently, the agent iteratively adjusts the network parameters to improve the approximation of desired outputs. Through successful training, the agent becomes capable of providing correct answers to queries posed by the environment (Alom *et al.*, n.d.). Supervised learning encompasses a range of techniques employed in machine learning. These techniques include k-Nearest Neighbors (kNN), Decision Trees, Support Vector Machines (SVM), Naïve Bayes Classifier, Linear Regression, Nonlinear Regression (Omary & Mtenzi, 2010), boosted trees, decision trees, bagged trees, Artificial Neural Networks, memory-based learning, random forests, and boosted stumps (Caruana & Niculescu-Mizil, 2006), etc.

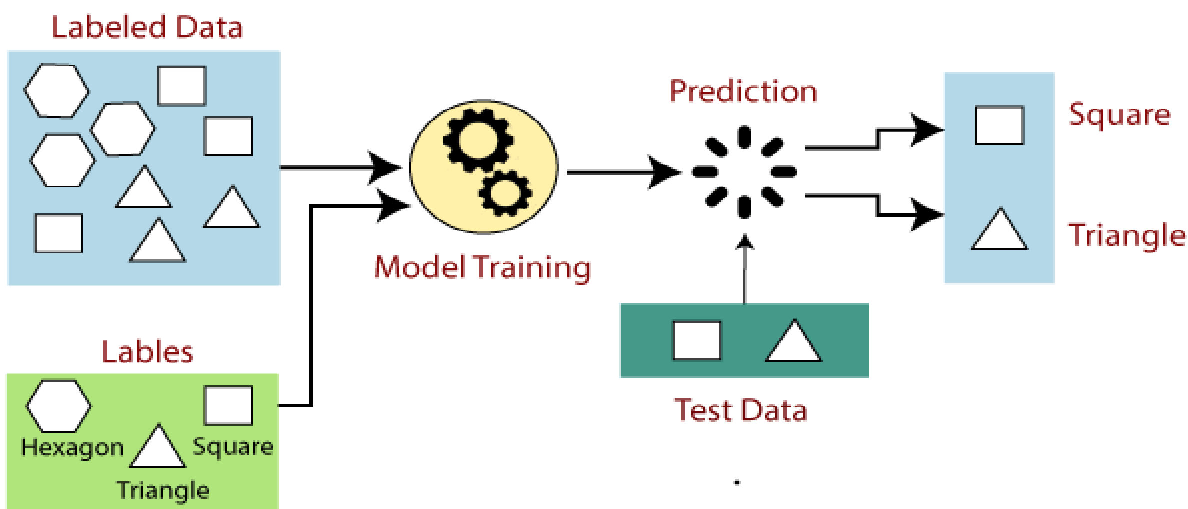

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Figure 5: Supervised learning

Source: (*Supervised Machine Learning - Javatpoint*, n.d.)

1.2.2 Semi-supervised Learning

It is a branch of machine learning that utilizes both labeled and unlabeled data to accomplish learning tasks. Positioned between supervised and unsupervised learning, it enables the utilization of abundant unlabeled data alongside comparatively smaller sets of labeled data, allowing for more comprehensive learning in many scenarios (van Engelen & Hoos, 2020). Semi-supervised learning techniques often incorporate Generative Adversarial Networks (GANs) and Deep Reinforcement Learning (DRL) in certain situations. Furthermore, Recurrent Neural Networks (RNNs), including LSTM and GRU, are also employed as part of semi-supervised learning approaches (Alom *et al*., n.d.).

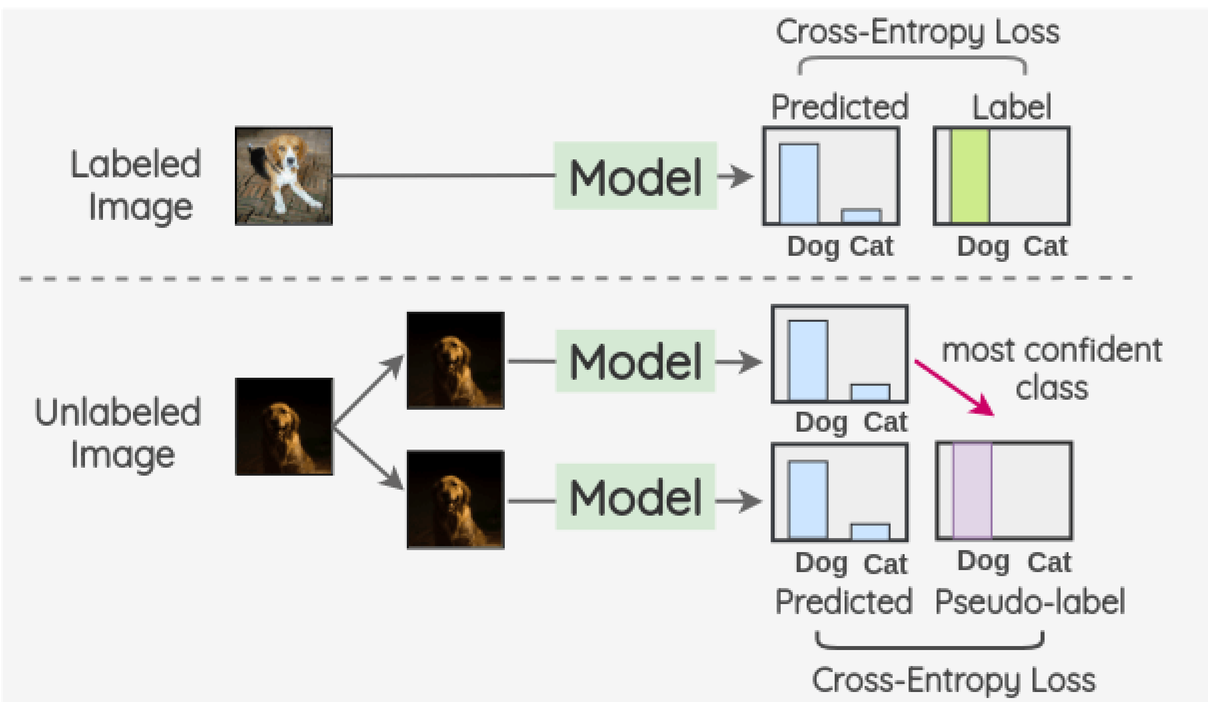


Figure 6: Semi-supervised learning

Source: (Chaudhary, 2020)

1.2.3 Unsupervised learning

Unsupervised learning systems operate without relying on data labels. They are tasked with inferring a function to uncover the underlying structure from unlabeled data. In other words, these learning algorithms do not have any labels to guide the learning or training process. Instead, they are provided with a substantial amount of data and the characteristics of each observation as input, without any desired output. Unsupervised learning is commonly used, for example, in clustering tasks, where images are divided into distinct sets or clusters based on inherent features such as color, size, shape, and more (Dike *et al*., 2018). Besides data clustering, unsupervised learning encompasses various other techniques, such as hierarchical learning, latent variable models, dimensionality reduction, outlier detection, and knowledge acquisition, among others (Usama *et al*., 2019).

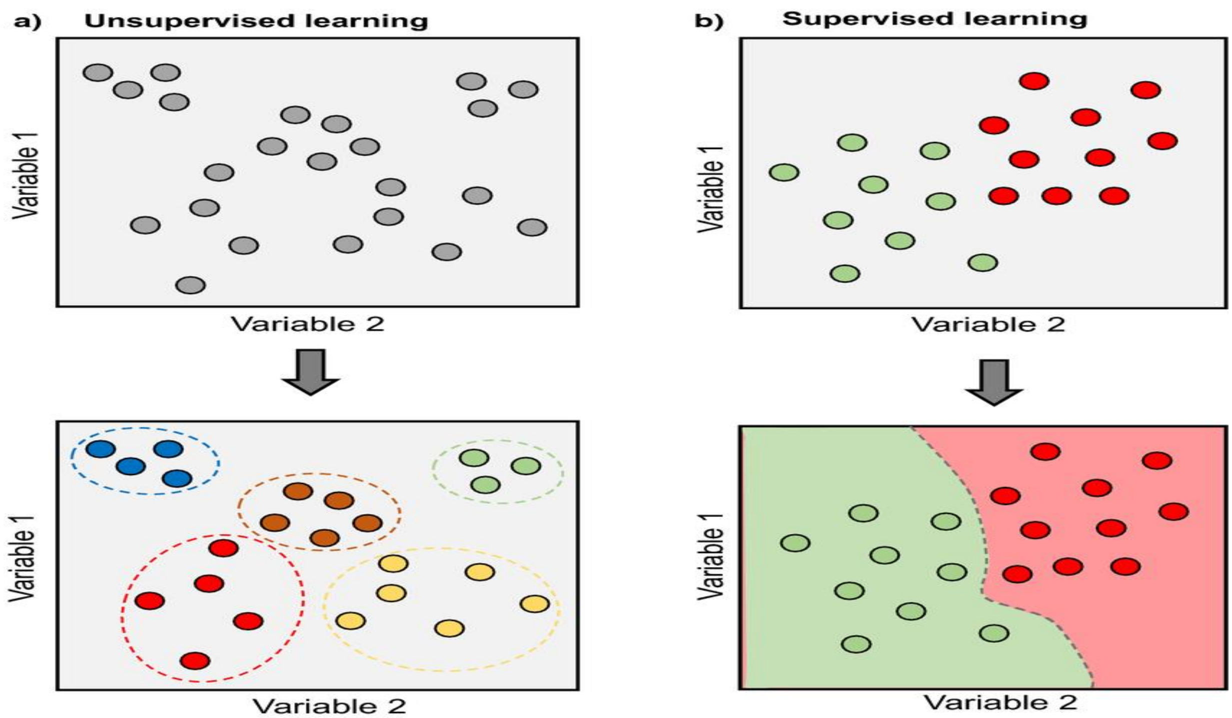


Figure 7: description of supervised and unsupervised learnings

Source: (Morimoto, 2021)

1.2.4 Deep Reinforcement Learning (DRL)

It is an approach to learning that merges the principles of reinforcement and deep learning. At present, the utilization of deep learning has expanded the capabilities of reinforcement learning, enabling it to tackle complex problems that were once considered unsolvable. For example, deep reinforcement learning has made it possible to teach machines to play video games solely by analyzing pixel data. Moreover, this technique has found practical applications in robotics, where algorithms can learn control strategies directly from real-world camera inputs (Arulkumaran *et al*., 2017). Suppose the environment generates input samples xt according to a distribution ρ, and the agent predicts $\hat{y}t$ using a function. The agent receives a cost ct based on the probability distribution. The environment poses questions to the agent and provides noisy scores as answers. This technique is also called semi-supervised learning. Numerous techniques, both unsupervised and semi-supervised, have been created based on this concept. RL poses challenges in learning due to the absence of a direct loss function, making it more difficult in comparison to usual supervised approaches. The fundamental distinctions between RL and supervised learning are as follows: first, access to the function being optimized is not readily available; it must be obtained through interaction.

The choice of RL type depends on the problem's scope or space. If the problem requires optimizing a large number of parameters, Deep Reinforcement Learning (DRL) is the recommended approach. On the other hand, if the problem involves a smaller number of parameters, a derivative-free RL approach is suitable.

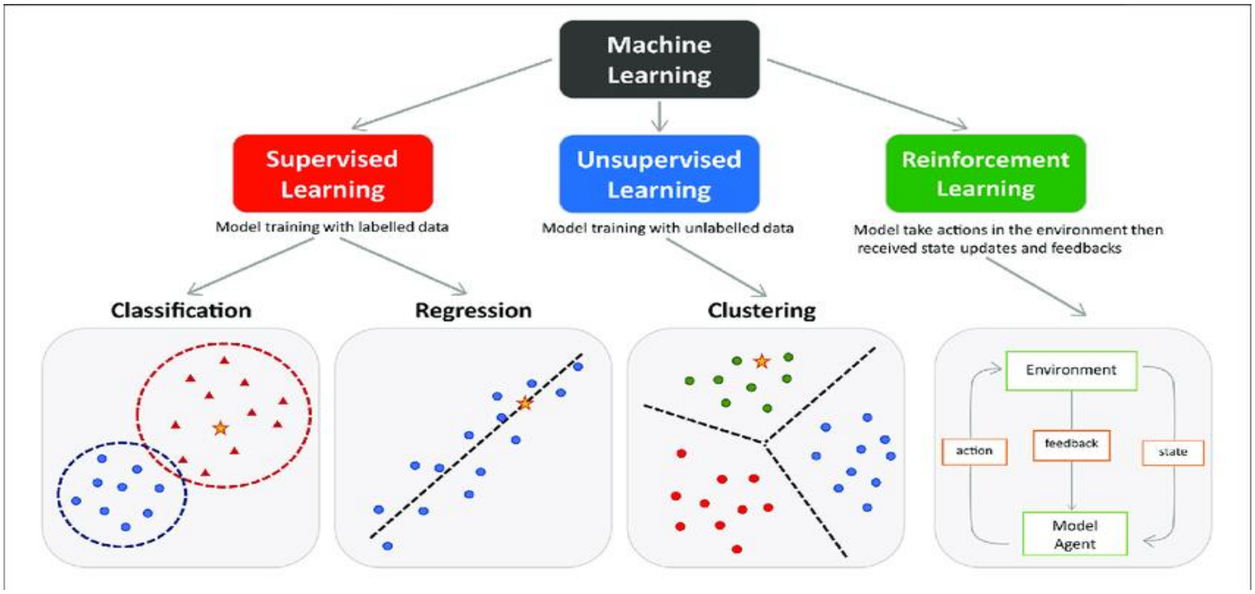


Figure 8: Deep Reinforcement Learning

Source: (Peng *et al*., 2021)

1.2.5 Feature Learning

One crucial distinction between deep learning (DL) and traditional machine learning (ML) lies in the process of feature extraction (Lai, 2019). In traditional machine learning (ML) methods, manual feature engineering is employed, utilizing various feature extraction algorithms such as Histogram Oriented Gradient (HOG), Speeded Up Robust Features (SURF), Empirical mode decomposition (EMD) for speech analysis, Scale Invariant Feature Transform (SIFT), Local Binary Pattern (LBP) and others. These extracted features are then fed into learning algorithms like support vector machine (SVM), Principal Component Analysis (PCA), Random Forest (RF), Linear Decrement Analysis (LDA) and others for classification. Boosting techniques are also commonly utilized, where many learning algorithms are applied to the features of a specific dataset or task, and a decision is made based on the outcomes of these algorithms.

In contrast, deep learning (DL) takes a different approach. It automatically hierarchically learns features across multiple levels. This ability to automatically learn features is a significant advantage of deep learning over traditional machine learning methods.

To establish the relationship between soil classes or qualities and their environmental elements in digital soil mapping (DSM), numerous machine learning models have been developed. Most of these models are trained using the supervised learning (SL) method, which makes use of training samples (Zhang *et al*., 2021).

1.3 Challenges of DL in agriculture

Similar to any other algorithm, deep learning also comes with its own set of challenges and limitations. Deep learning has difficulties when working with low-quality images that have fewer colors, incomplete information, or a limited amount of data. Additionally, deep learning is computationally expensive, and the representations learned from deep learning can be challenging to interpret and understand.

Increasing the number of layers or using larger training datasets can introduce additional issues. Another problem arises from the absence of standardized protocols for handling various types of data collected from different devices and employed in diverse applications. The reliance on deep learning on vast amounts of data necessitates the development of efficient techniques to manage the ever-growing data generated by the Internet of Things (IoT) or internet-connected devices. Deep learning algorithms excel at mapping inputs to outputs but struggle with comprehending the contextual nuances within the data they process. Overfitting, hyperparameter optimization, the need for high-performance hardware, and limited flexibility are other notable challenges faced in deep learning (Tyagi & Rekha, 2020).

While deep learning algorithms present promising opportunities for soil characterization and crop recommendation in agriculture, they also encounter various challenges and limitations that must be addressed for their effective implementation. This section will explore key challenges and limitations associated with deep learning algorithms in agricultural applications.

A significant hurdle in agricultural applications is the limited availability of high-quality data required for training deep learning models. Agricultural datasets often suffer from issues like data scarcity, class imbalance, and missing or noisy data. Insufficient data can negatively impact the performance and generalization ability of deep learning algorithms (Albahar, 2023).To overcome this challenge, it is essential to collect large-scale, diverse, and representative datasets that adequately represent the agricultural context.

Often, deep learning models as considered black-box, making it difficult to comprehend and interpret their decision-making processes. The lack of interpretability and explainability in deep learning algorithms hinders their adoption in critical agricultural decision-making tasks. Farmers and domain experts require transparent and interpretable models to gain insights and trust in the recommendations provided (Mohanty et al., 2016). It is crucial to invest research efforts in developing techniques that enhance the interpretability of deep learning models specifically tailored for agricultural applications.

1.4 Gradient descent

It is an optimization technique used to discover the local minima of a function that is differentiable, aiming to minimize the value of the loss function. It operates by iteratively adjusting the parameters in the opposite direction to the gradient of the objective function (Dogo *et al*., 2018). It is employed for training Artificial Neural Networks (ANNs) by utilizing Rectified Linear Units (ReLU) as the activation function (Jentzen & Riekert, 2021).

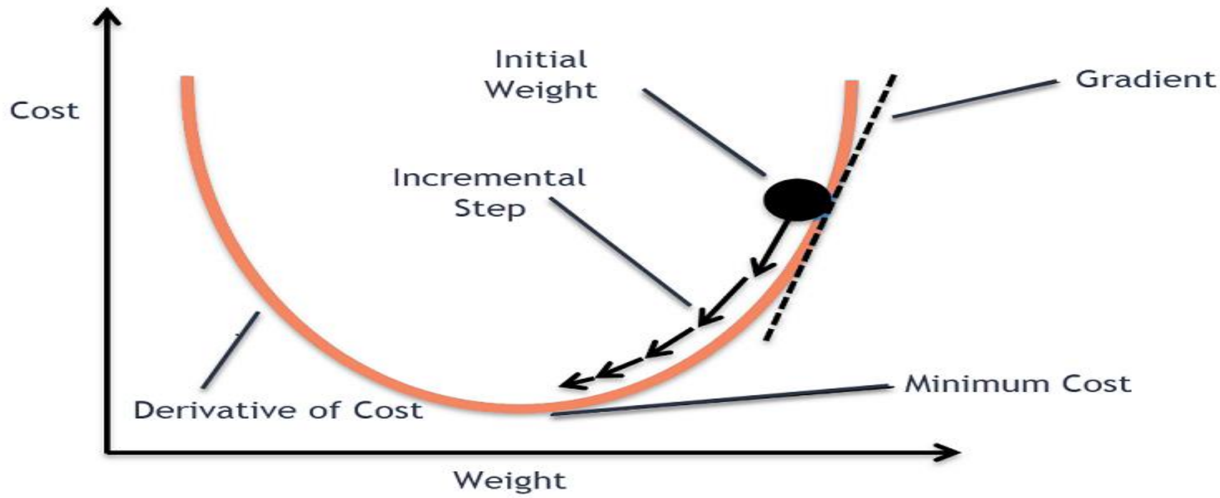


Figure 9: description of gradient descent Algorithm

Source: (Crypto1, 2020)

1.5 Back-propagation

The back-propagation algorithm is the predominant method utilized for training Neural Networks (Phansalkar & Sastry, 1994). Once the weights are initially assigned randomly, the backpropagation algorithm takes over and iteratively adjusts them until the losses reach a sufficiently small level. It can be divided into four (4) distinct steps:

- Forward pass
- Backpropagation to the output layer
- Backpropagation to the hidden layer
- Weight updates (Cilimkovic, n.d.).

1.6 Momentum

Momentum is a strategy utilized in optimization algorithms to improve the learning process by promoting consistent weight updates in a specific direction. It helps accelerate learning, especially in situations characterized by small yet noisy gradients, wide curvatures or stable gradients. The primary objective of momentum is to facilitate swift learning in challenging scenarios (Haji & Abdulazeez, 2021). Furthermore, it can aid the network in bypassing local minima (Qian, 1999). In gradient descent algorithms, the updates to the weights are typically determined based on the of the loss function's gradients concerning the weights. However, this approach can occasionally lead to oscillations or sluggish updates in specific directions, resulting in slower convergence. To tackle this issue, momentum is introduced as a solution. Momentum incorporates a "momentum term" that accumulates gradients from previous updates and influences the direction of future updates. By incorporating momentum, the algorithm can address oscillations and promote smoother and faster convergence (Yakoubi *et al*., 2023).

1.7 Learning rate (η)

The learning rate plays a critical role in training deep neural networks as it determines the size of the steps taken during the training process, affecting its speed. However, selecting the appropriate learning rate is essential. If the learning rate is set too high, it may cause the network to diverge instead of converging. Conversely, setting the learning rate too low can lead to slow convergence and the network becoming trapped in local minima. To mitigate this issue, it is common to reduce the learning rate during the training process. (Bottou & Laboratories, n.d.).

1.8 CNN overview

The Convolutional Neural Network (CNN) is a type of deep learning model designed mainly to process images. It draws inspiration from the organization and structure observed in the visual cortex of animals (Hubel & Wiesel, 1968). The initial proposition of the Convolutional Neural Network (CNN) was introduced by Fukushima in the year 1988(Fukushima, 1988). A Convolutional Neural Network (CNN) is a mathematical model that typically comprises three fundamental components: convolution, pooling, and fully connected layers. The pooling and convolution layers play a vital role in extracting relevant features from the input data, while the fully connected layer maps these extracted features to the final output, often used for classification purposes. A convolution layer in a CNN is made up of a series of mathematical operations, including the convolution, a specific kind of linear operation. When processing digital images, where pixel values are organized in a 2D grid, a small grid of adjustable parameters known as a kernel or feature extractor is applied to each position in the image. This characteristic enables CNNs to efficiently process images, as features can be detected at any location within the image. The retrieved features may progressively get more complicated as one layer's output feeds into the next. Training, which entails decreasing the difference between the network's anticipated outputs and the actual ground truth labels, is the process of optimizing parameters, such as kernels. Backpropagation and gradient descent are common techniques used to accomplish this optimization (Yamashita *et al*., 2018).

1.8.1 Convolution Layer

One of the most important parts of CNNs is the convolution layer, which combines linear and non-linear processes to extract features (Yamashita *et al*., 2018). Learnable kernels are employed to convolve feature maps obtained from previous layers. The final step in processing the output is an activation function, which can be either linear or non-linear and include functions like sigmoid, hyperbolic tangent, Softmax, rectified linear, or identity. This process generates output feature maps. Multiple input feature maps can be combined with these output feature maps. Separate kernels are utilized to convolve the input maps, resulting in corresponding output maps. Following activation functions, such as sigmoid, hyperbolic tangent, Softmax, rectified linear, or identity functions, these output maps might be linear or non-linear (Alom *et al*., n.d.).

1.8.2 Pooling layer

In order to generate new feature maps with a lower resolution, the pooling layer is essential for downsampling the feature maps from the layer before. This procedure accomplishes two key goals. First off, it lowers the quantity of parameters or weights, which lowers the cost of computation. Second, it aids in reducing network overfitting. An efficient pooling technique seeks to extract only crucial data while ignoring extraneous specifics. The pooling action in Deep Neural Networks can be implemented using a variety of methods. These strategies can be divided into two categories: well-liked methods and new methods. LP Pooling, Stochastic Pooling, Spatial Pyramid Pooling, and Region of Interest Pooling are a few of the well-liked techniques. Other approaches include Average Pooling, Max Pooling, Mixed Pooling, and Mixed Pooling. However, the unique techniques also include multi-scale order-less (Gholamalinezhad & Khosravi, n.d.).

1.8.3 Classification Layer

This section discusses the fully connected layer in a CNN, which determines the class scores using the characteristics that were taken out of a previous convolutional layer. The fully connected layers that function as a softmax classification layer receive the feature maps from the final layer as vectors with scalar values. Although the number of layers in the network model is not fixed, other methods like global average pooling and average pooling have been suggested to dramatically lower the number of parameters in the network due to the computational difficulty of fully linked layers.

The typical method used in fully connected neural networks (FCNN) is used to update the completely connected layers during the backpropagation phase of CNNs. By executing a full convolution operation on the feature maps between the convolutional layer and its immediately preceding layer, the filters in the convolutional layer are updated (Alom *et al.*, n.d.).

1.9 AI for soil classification

The use of machine learning (ML) technologies in soil sciences is increasing, particularly in industrialized countries. Physical characteristics, soil organic carbon, remote sensing, water contamination, erosion, parent material, neural networks (NN), support vector machines (SVM), spectroscopy, class modeling, ensemble methods, crops, and continuous modeling are among the 12 categories that can be used to categorize the use of AI in soil science (Padarian *et al.*, 2020). For instance, Srivastava et al. (2021) applied Convolutional Neural Networks (CNNs) to classify soil samples based on hyperspectral images. They trained the CNN model on a large dataset of soil samples and achieved impressive accuracy in identifying different soil types. The use of CNNs allows for automatic feature extraction and hierarchical learning, eliminating the need for manual feature engineering and domain-specific knowledge. This approach has shown promising results and has the potential to revolutionize soil classification methodologies in the future (Srivastava *et al.*, 2021). In order to forecast and predict the spatial and temporal patterns of daily soil moisture, O. and Orth created and trained a Long Short-Term Memory (LSTM) model in 2021. Over 1,000 global monitoring stations' in-situ data were used to train the algorithm (O. & Orth, 2021). Recently, Singh and Gaurav introduced a unique architecture that calculates surface soil moisture using a fully linked feed-forward ANN model. This method was notably used on the large Kosi River alluvial fan area in the Himalayan Foreland. They collected nine unique features, including dual-polarized radar backscatter from Sentinel-1, red and near-infrared bands from Sentinel-2, and a digital elevation model from the Shuttle Radar Topographic Mission, from a variety of satellite products. These characteristics were acquired using graphical indicators and linear data fusion. To evaluate the significance of each feature on the response variable, they conducted a feature importance analysis using the regression ensemble tree approach, as well as assessed feature sensitivity (Singh & Gaurav, 2023). Similar to this, Heuvelink et al. used quantile regression forest machine learning techniques to anticipate Argentina's yearly soil organic carbon (SOC) stock at a depth of 0-30 cm with a resolution of 250 m from 1982 to 2017 (Heuvelink *et al.*, 2021). InCeres, a startup in the agricultural sector based in Brazil, has created a mobile application capable of forecasting soil quality and fertility. This prediction is derived from data related to soil composition, weather patterns, crop varieties, and satellite imagery that indicates plant growth rates. The app combines these inputs to provide an analysis of soil application and nutrient uptake (Ali, 2022). In the last 2021, Chatterjee *et al.* carried out a comparative assessment to evaluate the performance of different convolutional neural network (CNN) architectures, specifically ResNet50, VGG19, MobileNetV2, VGG16, NASNetMobile, and InceptionV3. Their objective was to classify four soil types: Clay, Black, Alluvial, and Red. Among these models, ResNet50 demonstrated the highest performance, achieving a training accuracy of 99.47% and a training loss of 0.0252. In comparison to the other considered models, ResNet50 exhibited superior classification capabilities *(*Chatterjee *et al.*, 2021).

Convolutional Neural Networks (CNNs) have found extensive use in tasks related to characterizing soils through image analysis. CNNs are specifically designed to autonomously learn hierarchical representations from input images, enabling them to effectively capture spatial features and patterns present in soil images. These models have demonstrated notable success in tasks like soil classification, utilizing image data to achieve impressive levels of accuracy (Kamilaris & Prenafeta-Boldú, 2018).

However, none of those has used deep learning to develop a model that can classify soil types based on French classification system in order to build a system for agricultural soil identification and crop recommendation.

Chapter 2: materials and methods

2.1 Study Area

Niger Republic is an African country located in west Africa. The region of Maradi, namely the area between 13° and 15°26' North Latitude and 6°16' and 8°36' East Longitude, is the subject of this study, which is located in the middle southern section of Niger. It is bordered by the Zinder region to the east, the Tahoua region to the west, the Agadez region to the north, and the Federal Republic of Nigeria to the south, with a boundary that stretches for about 150 kilometers. It has a total size of 41,796 square kilometers.

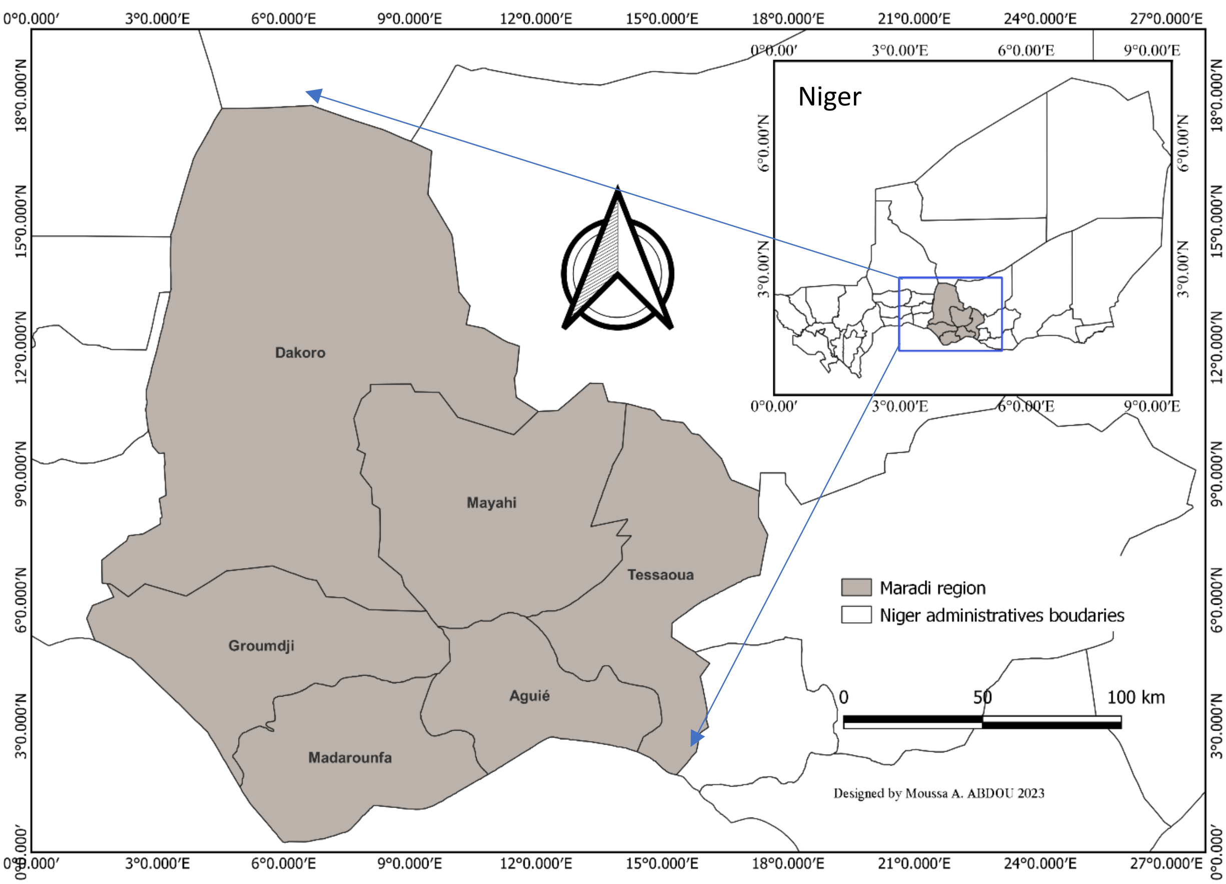


Figure 10: Study area

2.1.1 Human Environment

According to the National Institute of Statistics of Niger, the Maradi region has a population of 4160231 individuals in 2018 (INS, 2018). The population density in Maradi was 81.4 inhabitants per square kilometer. The majority of the region's residents (86.3%) live in rural areas. Women make up 50.8% of the population, with a total of 1,728,311 women. The population of the Maradi region is notably young, with 54.4% under the age of 18 (compared to 51.6% nationwide), and is experiencing slower growth than the national average (3.7% for the region compared to 3.9% for the country). The main economic activities in the region include agriculture, livestock breeding, trade, and handicrafts, primarily conducted within the informal sector (conseil regional de Maradi, 2015).

2.1.2 Agricultural Sector

Agriculture is the primary economic activity in the Maradi Region, engaging more than 95% of the rural population. Approximately 85% of the region's total population relies on agriculture as their main source of livelihood. The agricultural population is estimated to be around 2,112,385 individuals, residing in 300,102 households. Of these households, 3% are headed by women, each supported by 3 to 4 agricultural workers. The region's cultivable land resources are estimated to span 2,476,680 hectares. Fallow land has become scarce within production systems, particularly in the South, where land occupation exceeds 80% (conseil regional de Maradi, 2015).

The agricultural production zone of the region extends from the Middle Tarka Valley in the north to the border with the Federal Republic of Nigeria in the south, occupying the agroecological zone between the isohyets of 350 mm and 700 mm. Rainfed cereal crops, such as millet and sorghum, dominate the agricultural landscape, accounting for over 90% of cultivated areas. These crops are often intercropped with legumes like cowpeas and groundnuts. Cash crops, including Souchet, groundnuts, cowpeas, sesame, and sorrel, are cultivated either independently or in conjunction with cereals. Tobacco production is concentrated in the Goulbi Maradi Valley in Madarounfa (conseil regional de Maradi, 2015).

The Maradi region boasts significant irrigable potential, with over 47,000 hectares suitable for irrigation. Currently, more than 15,000 hectares are already irrigated, and flood-recession crops are cultivated along the entire Goulbi Maradi valley. Within the hydro-agricultural context, Maradi possesses 954 hectares of irrigated land with complete water control in Jirataoua. The dominant agricultural production systems in the region are as follows:

- Extensive system located between the Tarka Valley and the Goulbi N'Kaba;
- Semi-intensive system south of the Goulbi N'Kaba;
- Semi-intensive agricultural production system utilizing traditional irrigation;
- Intensive system implemented in private and public hydro and public areas (Djirataoua).

In the southern part of the region, agriculture, and livestock farming are tightly integrated. Practices such as plowing and small-scale hut farming are common, along with the utilization of agricultural by-products as livestock feed. Additionally, farmers employ manure and/or compost to improve soil quality (conseil regional de Maradi, 2015).

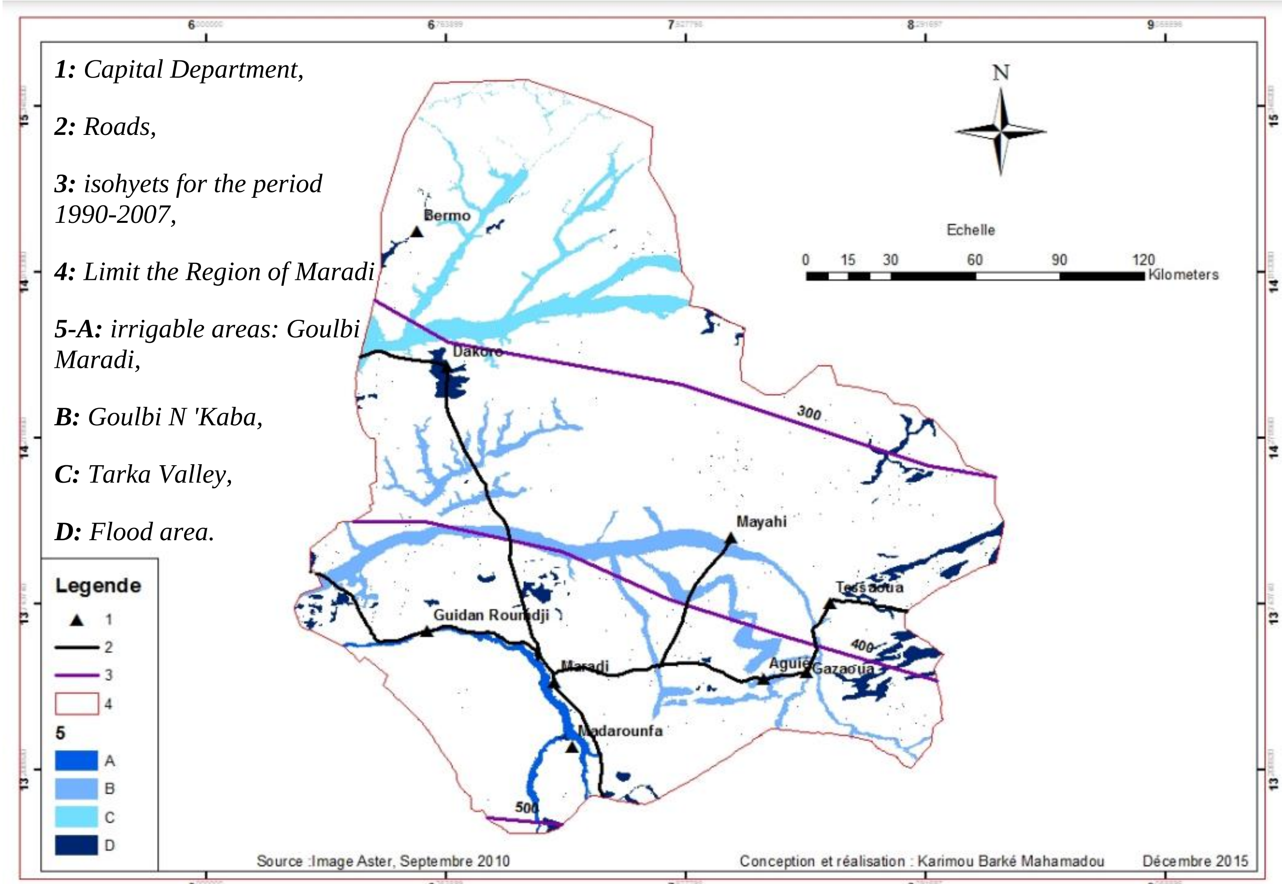


Figure 11: Areas of strong agricultural potential

Source: (Moumouni, 2015)

2.1.3 Climatic and agro-ecological factors

The Maradi region possesses substantial surface and groundwater resources. Surface water sources in the region primarily consist of rivers with seasonal flow patterns, such as the Goulbis and the Tarka, as well as a series of permanent pools like Lake Madarounfa, Tarka pools, and other semi-permanent pools, fossil valleys, and mini-dams. These watercourses and pools play a vital role in the region's water supply.

Regarding groundwater resources, the Maradi region encompasses three main aquifer systems: the Hamadian Continental aquifer system, the discontinuous aquifers of the South Maradi basement, and the alluvial aquifers of the Goulbi and Tarka rivers. These groundwater sources hold significant importance for the region.

Considering the Tarka aquifers, which have limited coverage due to precipitation and vegetation factors, the Maradi region can be divided into three biogeographical zones with complementary characteristics:

Saharan-Sahelian Zone: This zone receives rainfall ranging from 200 to 300 mm annually

Sahelian Zone: With rainfall between 300 and 600 mm per year, this area serves as an agropastoral and agricultural zone

Sahelo-Sudanese Zone: This zone boasts abundant forest and wildlife resources, with rainfall exceeding 600 mm annually (conseil regional de Maradi, 2015).

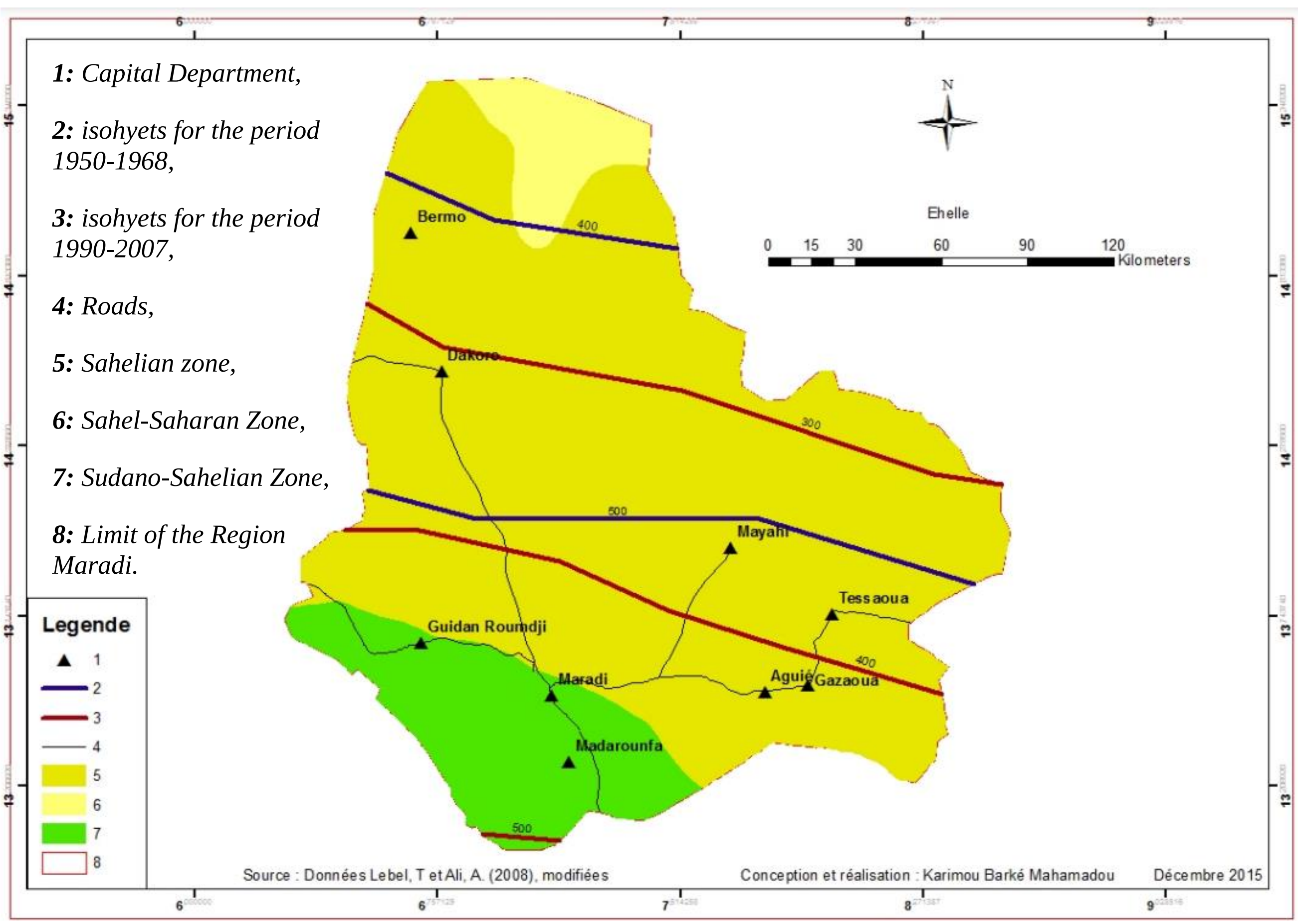


Figure 12: Map of climatic zones in the Maradi region. ***Source:*** *(Moumouni, 2015)*

2.2 Data Collection

To identify the types of the study area's soil, a meticulous process was undertaken. A precise pedological map has been used interactively on QGIS. This map played a crucial role in identifying the various soil types present within the region, forming the foundation for further analysis. Subsequently, specific focus was placed on the agricultural soil types prevalent in the area, as they directly impact agricultural practices. Five types of agricultural soil types were identified and located using QGIS by overlaying villages layer which was used to select only villages with 200 or more household. Over the scope of each soil type, one or more villages closest to the center of the area were selected proportionally. Images of the soils were taken under natural conditions using smartphone cameras. This collection of images constituted a valuable database used for training, validating and testing the models. In addition to images, survey data was diligently gathered to gain insights into traditional soil usage in the area. The survey data, together with the image database, provided a multifaceted understanding of the soil's characteristics and historical utilization patterns. To further enhance the investigation, samples of the soil were collected through pedologic pit digging on each of the identified sites. The collected soil samples are sent to laboratory for rigorous analysis. This comprehensive data collection process lays a solid foundation for the subsequent analysis and interpretation of the study area's soil characteristics, contributing significantly to the overall research objectives of this thesis.

Table 1: Types of data

Description	Format	Source
Pedological data: Soil classification data based on the French classification system	Shapefile (shp)	University of Diffa
Soil Images data: Images of each of the concerned types of soil have been taken using smart phones	Joint Photographic Experts Group (jpg)	Field
Laboratory samples soil data: Results of soil samples analysis taken from the field	Comma-separated values (CSV)	INRAN/Niamey
Soil usage data: Data on traditional uses of soil by farmers	Comma-separated values (CSV)	Field

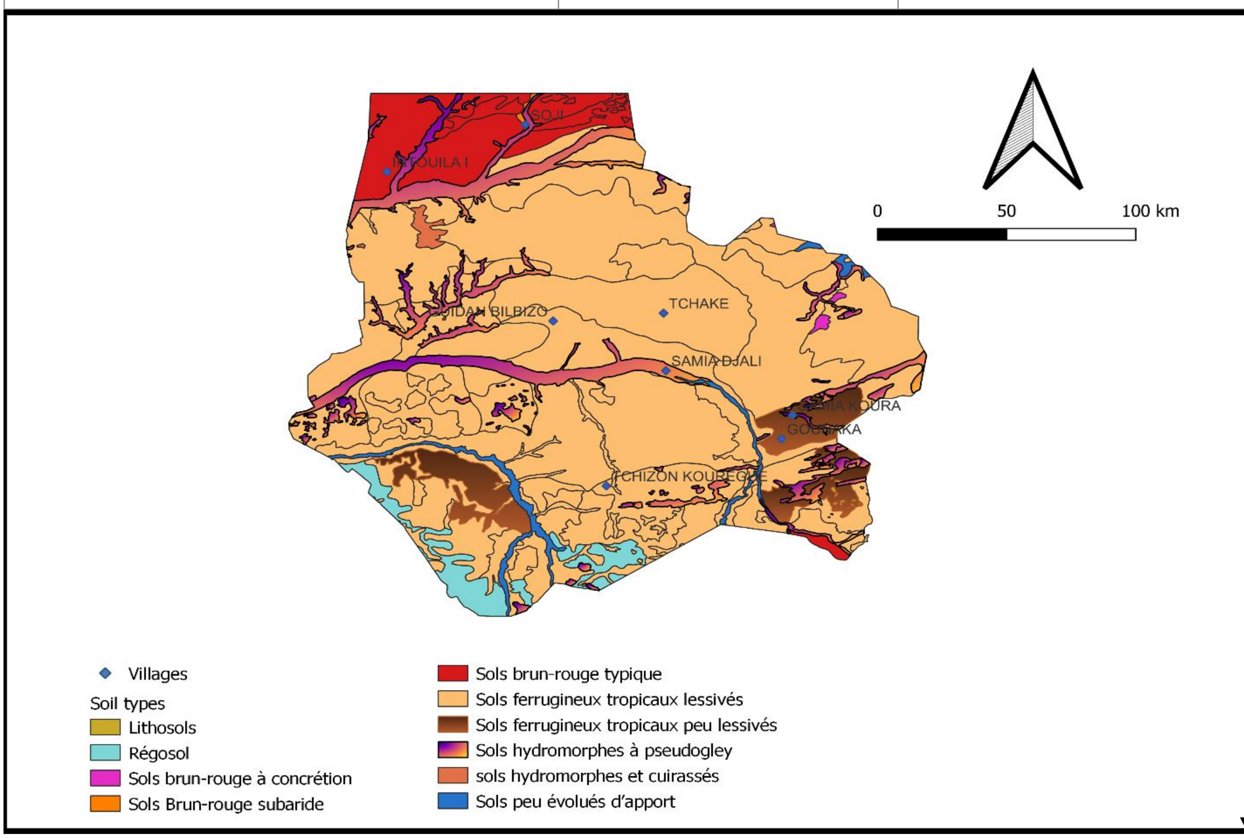


Figure 13: Pedological map of the study area

2.3 Material and Tools

The materials used within the framework of the study include the following on one hand:

Daba and shovel: to dig the pedological trenches;

Tape measure: to measure de depth of the pedological pit;

Smartphones: to collect soil images;

GPS: to check the location

On the other hand, open-source tools were dominant in this study. Python, an interpreted programming language known for its versatility, was employed. Jupyter Notebook, a programming interface based on JSON and designed for interactive computing, served as the open document format utilized in the research. QGIS, an application for desktop geographic information systems. It operates across multiple platforms and offers features for the visualization, modification, and examination of geospatial data. The study utilized QGIS for its functionalities.

The following libraries were imported in Python to perform the study:

TensorFlow: is a freely available software library created specifically to facilitate machine learning and artificial intelligence tasks. It is available at no cost and offers a wide range of applications, with a specific emphasis on the training and inference of deep neural networks. It has been used for model development.

Scikit-learn: previously known as scikits. learn and commonly referred to as sklearn, is a Python-based machine-learning library that is freely available. It is used main to generate the classification report.

Matplotlib: Matplotlib is a versatile Python library that offers a wide range of capabilities for generating static, dynamic, and interactive visualizations. It has been employed to plot the graphs.

Pandas: is an open-source data analysis and manipulation tool that is built on the Python programming language. It offers a combination of speed, strength, flexibility, and user-friendliness, making it a valuable tool for handling and processing data efficiently.

NumPy: is a Python library that enhances the capabilities of the programming language by providing support for vast, multi-dimensional arrays and matrices. Additionally, it offers an extensive collection of advanced mathematical functions that are specifically designed to work efficiently with these arrays.

Pillow: (The Python Imaging Library) is freely available and open-source and is an additional library for the Python programming language. It extends the functionality of Python by introducing support for various image file formats, enabling users to effortlessly open, manipulate, and save images in different formats.

Flask: is an open-source Python web development microframework. It is categorized as a microframework because it is lightweight. Flask aims to maintain a simple yet extendable core. It does not include an authentication system, a database abstraction layer, or a form validation tool. However, numerous extensions are available to easily add these functionalities.

Werkzeug: is a comprehensive library for building web applications using the WSGI (Web Server Gateway Interface) standard. It originated as a modest assortment of different tools for WSGI applications but has evolved into one of the most sophisticated utility libraries for WSGI.

2.4 Methods

This thesis presents a robust methodology for identifying soil types using deep learning techniques following the below steps.

Data cleaning and Preprocessing: The collected data underwent a rigorous cleaning process to remove any noise or inconsistencies. Preprocessing techniques were then applied to prepare the data for subsequent model training.

Models' development: Eight different Convolutional neural networks (CNNs) architectures were employed as the primary models for soil type identification. The convolutional base of the pre-trained models was extracted in the case of transfer learning, it was combined with the top layers. This approach allowed for leveraging the knowledge learned from existing models while adapting them to the specific soil identification task.

Hyperparameters Optimization and Model Compilation: To ensure optimal model performance, hyperparameters were fine-tuned. This involved systematically adjusting various parameters and compiling the model to define the variables at their optimal states before training.

Model Training, Validation, and Testing: The models were trained using the prepared dataset, with a focus on minimizing error and maximizing accuracy. Training, validation, and testing datasets were carefully defined and utilized to assess the performance of the models at different stages. This iterative process helped identify potential issues and refine the models accordingly.

Application Development: A user-friendly web application was developed, utilizing the most accurate model identified after the training phase. This application allows users to input soil images for identification, providing valuable classifications and insights based on the trained model.

The presented methodology represents a comprehensive approach to soil type identification using deep learning. The accompanying figure visually summarizes the key steps involved in this research. Through extensive experimentation and evaluation, the proposed methodology demonstrates its effectiveness and potential for practical applications in soil identification using deep learning and related fields.

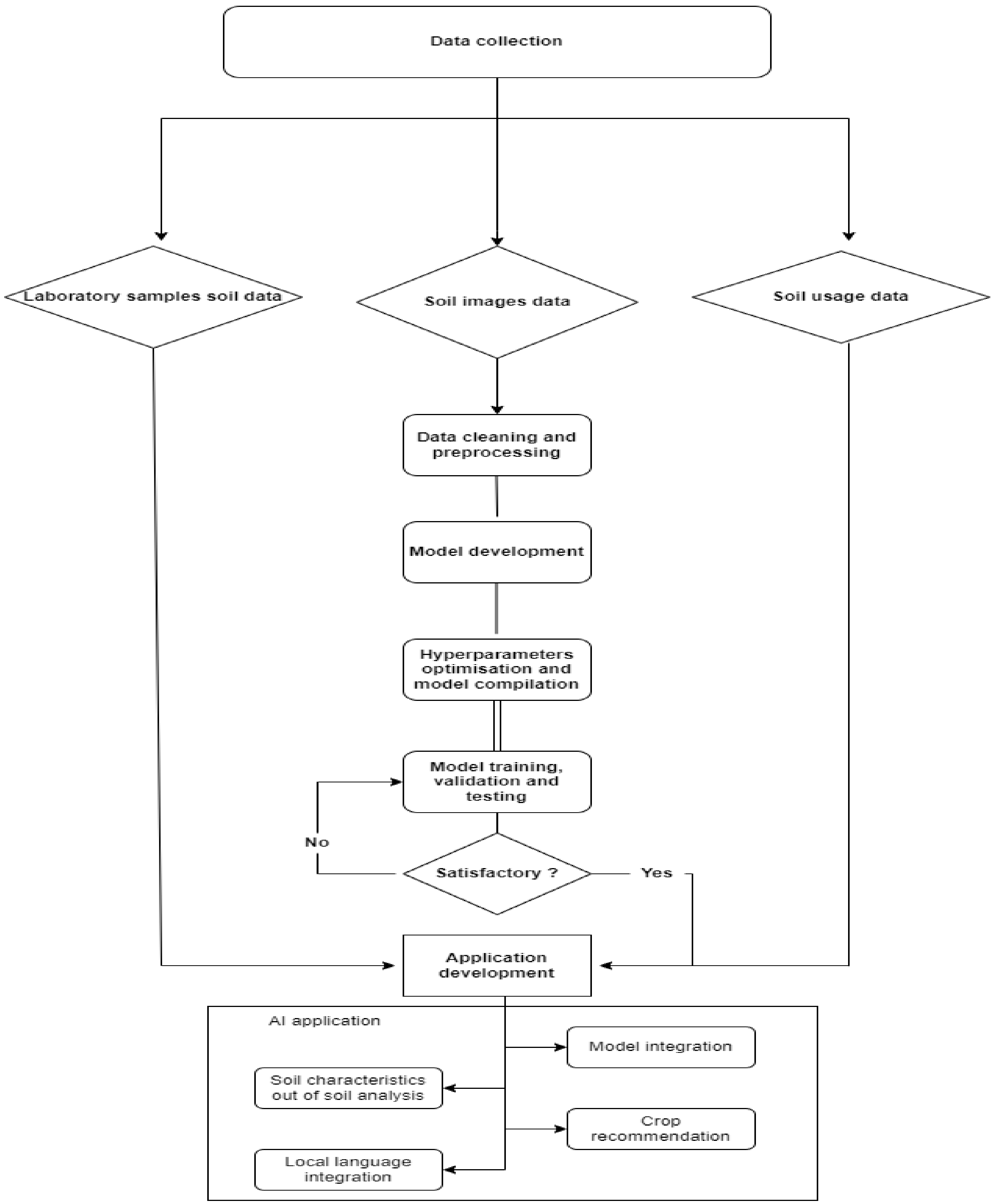


Figure 14: Flow chart of the methodology

2.4.1 Data Cleaning and Preprocessing

To ensure the quality and reliability of the collected data, a rigorous cleaning process was conducted, followed by other preprocessing techniques to prepare the data for effective model training. Several key steps were taken to enhance the integrity and usability of the dataset.

The preprocessing steps applied to the soil images data involved cleaning and transforming the images to ensure their suitability for the subsequent deep-learning models. The following steps were undertaken:

2.4.1.1 Manual Noise Identification and Noise Removal:

A visual inspection of the soil images was conducted to identify any noticeable noise or artifacts present in the images and remove any noise present in the images. To mitigate the impact of noise on the model's performance, a manual noise removal technique was applied.

2.4.1.2 Reshaping Images into Squared Shape:

The original soil images collected from the field may have varied dimensions, such as different heights and widths. To standardize the input for the deep learning models, it was necessary to transform the images into a squared shape. This transformation was accomplished using a Python script developed specifically for this research.

By applying these preprocessing steps, the soil image data was cleaned, standardized, and prepared for training the deep learning models. The noise removal step helped to enhance the quality of the images, reducing potential interference in the classification process. The transformation of the images into squared shapes ensured consistency in the input dimensions for the CNN models, enabling them to effectively learn and extract features from the soil images.

2.4.1.3 Dataset splitting

Next, to split the dataset into training, evaluation, and testing subsets, a Python script was developed. This script randomly divided the images into the following proportions: 75% for training, 20% for evaluation, and 5% for testing.

The dataset was balanced, with each of the five soil classes represented evenly. This balanced dataset was used to train and evaluate all the models.

The use of these datasets, both the balanced and unbalanced versions, enabled the training and evaluation of the different CNN models. The subsequent sections will present the performance analysis and discuss the results obtained from these experiments.

2.4.2 Model development

In the model-building phase, a comprehensive approach was taken to develop effective models for soil type identification. Eight different Convolutional Neural Networks (CNNs) architectures were utilized for this task. These architectures included seven popular CNN models that have been widely used and recognized for their performance in various computer vision tasks and a new architecture created specifically for this research, tailored to address the unique requirements of soil type identification.

The deep learning models created and compared in this research included a model created specifically for this study (referred to as "simple architecture") and seven pre-existing CNN architectures (Densenet201, MobileNetV3Large, VGG16, VGG19, InceptionV3, ResNet50, and Xception).

The first step in building the models involved extracting and freezing the convolutional base of the CNN architectures for the pre-existing models. This process enabled the utilization of pre-trained models and allowed for leveraging the knowledge and features learned from large-scale datasets in related domains. By extracting the convolutional base, the models gained a foundation of well-trained layers that could capture and extract relevant visual features from the soil images effectively.

In the case of transfer learning, the extracted convolutional base was combined with custom-designed top layers. This integration facilitated the adaptation of the pre-trained models to the specific task of soil type identification. The top layers were specifically designed to align with the soil classification output and capture the distinctive features and patterns relevant to different soil types.

The combination of leveraging existing popular CNN architectures and creating a customized architecture specifically for soil type identification provided a diverse set of models to explore and evaluate. This approach aimed to optimize the models' performance by leveraging established knowledge while adapting to the unique nuances of soil type identification while the novel architecture has been created using a sequence of five convolution and pooling layers before the dense layers were created to meet the specific need of the research.

For each of the models, the specific configuration of layers, such as the number of filters, kernel sizes, and activation functions, were determined based on the requirements of the soil type classification task. The hyperparameters were the same for each model's architecture as follows:

- Learning rate: 1e-4
- Batch size: 32
- Optimizer: RMSprop
- Regularization techniques: No regularization techniques were used.

Moreover, to monitor the training process and prevent overfitting, a Keras callback called `EarlyStopping` was utilized to train all models. This callback is designed to automatically stop the training when a certain condition is met. In this research, the `EarlyStopping` callback was configured as follows:

```
callback = tf.keras.callbacks.EarlyStopping(
    monitor="val_loss",
    patience=5,
```

restore_best_weights=True,

)

The callback was set to monitor the validation loss (`val_loss`) during training. It tracked the validation loss and made decisions based on its value. The `patience` parameter was set to 5, which means that if the validation loss did not improve for 5 consecutive epochs, the training process would be stopped.

Furthermore, the `restore_best_weights` parameter was set to `True`. This ensured that the weights of the model were reverted to the best weights obtained during training, based on the epoch with the lowest validation loss. This step was crucial to preserve the model's performance based on the optimal epoch, rather than the final epoch.

By incorporating the `EarlyStopping` callback, the research aimed to prevent overfitting, save computational resources, and identify the optimal point where the model achieved the best generalization performance on the validation set.

2.4.3 Hyperparameters Optimization and Model Compilation

The hyperparameters optimization and model compilation phase played a crucial role in achieving optimal performance for the models developed in this research. By fine-tuning the hyperparameters, various parameters were systematically adjusted to define the model variables at their optimal states before training commenced.

In this research, particular attention was given to setting the hyperparameters where several key hyperparameters were considered, including the batch size, learning rate, number of epochs, and the implementation of a Keras callback for early stopping.

The batch size, which determines the number of samples processed in each iteration during training, was carefully chosen to strike a balance between computational efficiency and model convergence. Through experimentation and validation, an optimal batch size was determined that allowed for the efficient utilization of computational resources while ensuring stable model convergence and accurate results.

The learning rate, a critical hyperparameter affecting the speed and quality of model training, was also optimized. By systematically adjusting the learning rate, the models were able to find the optimal direction for minimizing the loss function, resulting in faster convergence and improved model performance. This optimization process involved monitoring and validation to select the learning rate that achieved the best balance between training speed and model accuracy.

The number of epochs, indicating the total number of times the model iterates through the entire training dataset, was determined through the Keras callback function. The models underwent iterative training and validation to identify the optimal number of epochs that maximized model performance without overfitting or underfitting the data. This ensured that the models reached a stable and accurate state while avoiding excessive training that could lead to poor generalization of unseen data.

Overall, the hyperparameters optimization and model compilation phase aimed to fine-tune the models for optimal performance in soil type identification. Through careful selection and adjustment of hyperparameters, including the batch size, learning rate, number of epochs, and the utilization of a Keras callback for early stopping, the models were effectively configured to achieve accurate and reliable results.

By utilizing a diverse set of CNN architectures, including popular pre-trained models and a custom-designed architecture, the model's building phase ensured a comprehensive exploration of different model configurations. This approach aimed to achieve the highest accuracy and reliability in identifying and classifying soil types based on the visual features extracted from the soil images.

2.4.4 Model evaluation

The performance metrics used to assess the performance of the models for the specific soil type classification task included accuracy, loss, precision, recall, and F1-score. Each metric provides valuable insights into different aspects of the model's performance. Here's a brief explanation of each metric:

- **Accuracy:** Accuracy measures the proportion of correctly classified instances over the total number of instances. It provides an overall assessment of the model's ability to classify soil types correctly. A higher accuracy indicates better performance.
- **Loss:** Loss is a measure of the error between the predicted and actual soil type labels. It quantifies how well the model can fit the training data. The goal is to minimize the loss function, as lower values indicate better model performance.
- **Precision:** Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive (true positives + false positives). It assesses the model's ability to accurately identify soil types correctly. A higher precision indicates fewer false positives.

By evaluating these metrics, we gained a comprehensive understanding of the model's performance in classifying different soil types

2.4.5 Application Development

The application incorporated the most accurate model that was achieved during the training phase, ensuring reliable and precise results for users. It has been developed using python flask. In addition to the CNN algorithms, Natural Language Processing (NLP) has been used for the speak with the user and local language has been also integrated.

In fact, the primary objective of the application was to enable users to easily input soil images for identification and receive valuable insights based on the trained model. The application interface was designed with simplicity and user-friendliness in mind, ensuring that even non-technical users could navigate and utilize the system effectively.

Users will be able to upload or capture soil images within the application, which will then undergo a series of image-processing procedures. The trained model, integrated into the application's backend, receives the input images and executes the necessary computations to classify the soil types accurately, and displays the results in both text and speech.

To enhance the usability and reliability of the application, extensive testing and validation were conducted during its development. This process involved deploying the application with a diverse range of soil images and evaluating its performance against ground truth data.

Overall, the application development phase focused on creating a user-friendly platform that incorporated the most accurate model achieved during the training phase. By enabling users to input soil images and receive valuable insights after classification, the application aimed to provide a practical and accessible solution for soil type identification.

Chapter 3: Results and discussion

The purpose of this research was to help identify soil type and recommend crops to improve productivity. The study aimed to identify the most effective NN model for classifying soil types in the region and consequently build an AI-based application to facilitate real-time soil type classification in Maradi, Niger using the selected CNN model.

3.1 Results

The specific objectives of this research were as follows:

- Building different CNN models for soil type identification in Maradi, Niger: The initial task was to build various CNN and train them using the database.
- Compare different Convolutional Neural Network architectures for soil type classification: The second objective focused on evaluating and comparing different CNN architectures to determine the most suitable model for accurately classifying soil types in Maradi, Niger. The performance of these models was assessed based on various evaluation metrics, including accuracy, precision, recall, and F1-score. The aim was to identify the CNN architecture that yielded the highest accuracy and the most reliable results for soil type classification in the specific context of Maradi, Niger.
- Development of an AI-based application for soil type classification: The final objective of this research was to create a user-friendly application that integrates the chosen CNN model for real-time soil type classification. This application aimed to provide farmers, researchers, and other stakeholders in Maradi, Niger with a practical tool to identify soil types quickly and efficiently. Users could input images, and the model would classify the soil type based on the trained CNN architecture. The application was designed to be accessible and intuitive, facilitating seamless interaction between users and the deep learning model.
- Integrate local language in the classification system.

By comparing different deep learning models in the context of soil type classification, this research addresses a significant knowledge gap in the field. The study contributes to the advancement of agricultural practices in Maradi, Niger, by providing a reliable and efficient tool for identifying soil types. The findings from this research can aid farmers in making informed decisions regarding crop selection, land management, and soil fertility enhancement, ultimately leading to improved agricultural productivity and sustainability.

In the following sections, the results and discussion will present a comprehensive analysis of the performance of various CNN models for soil type classification in Maradi, Niger. The accuracy plots, training curves, classification reports, and other relevant metrics will be examined, comparing the models' performance and discussing their strengths and limitations. The findings will be discussed in the context of the research objectives and the potential applications of the identified best model and the developed mobile application.

3.1.1 Models development trends

The eight models have been successfully built as the following figures show the evolution of training and validation accuracy and loss. The x-axis represents the number of epochs while the y-axis represents the accuracy and loss value respectively for the left subplots and the right ones.

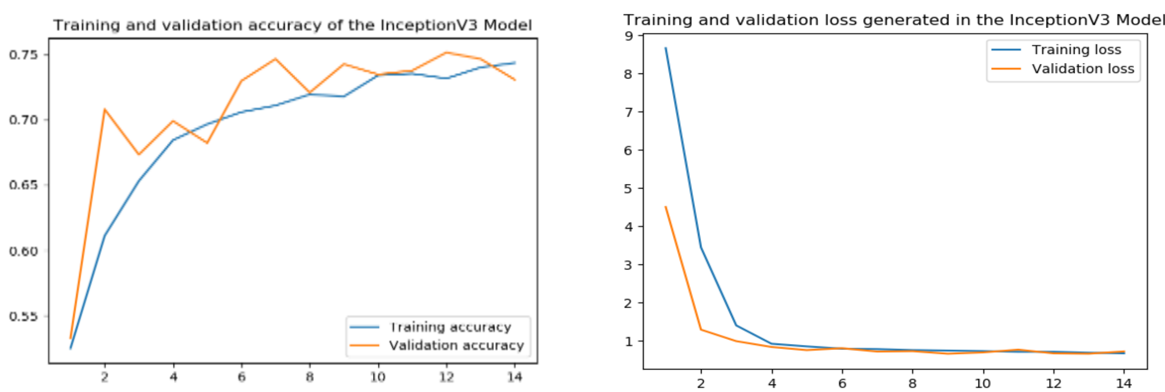


Figure 15: Training and validation accuracy and loss of InceptionV3

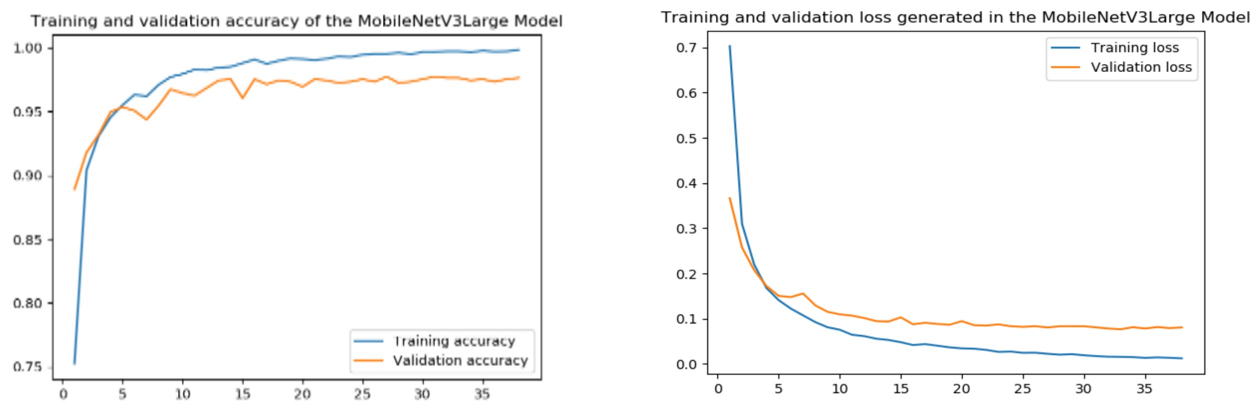


Figure 16: Training and validation accuracy and loss of MobileNetV3Large

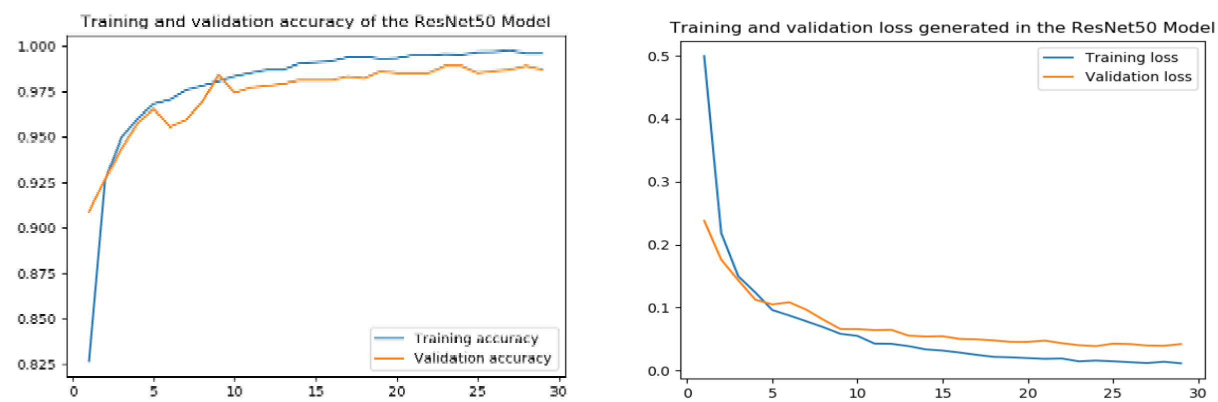


Figure 17: Training and validation accuracy and loss of ResNet50

Figure 18: Training and validation accuracy and loss of Simple_architecture

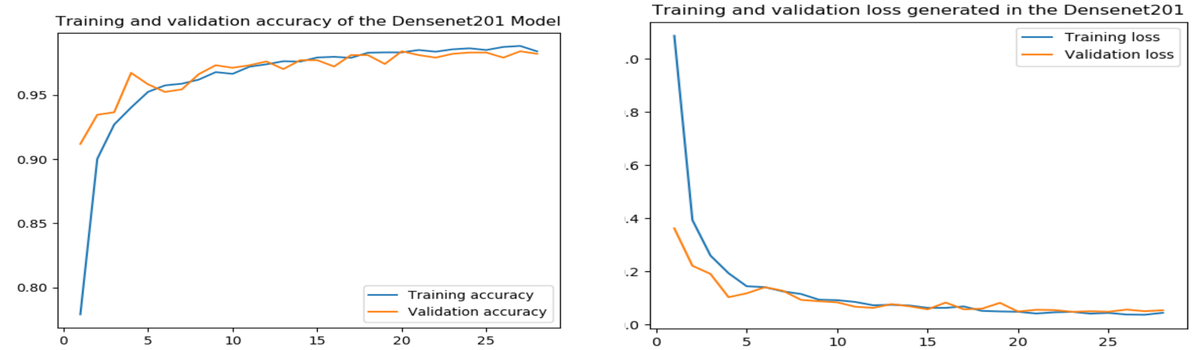


Figure 19: Training and validation accuracy and loss of Densnet201

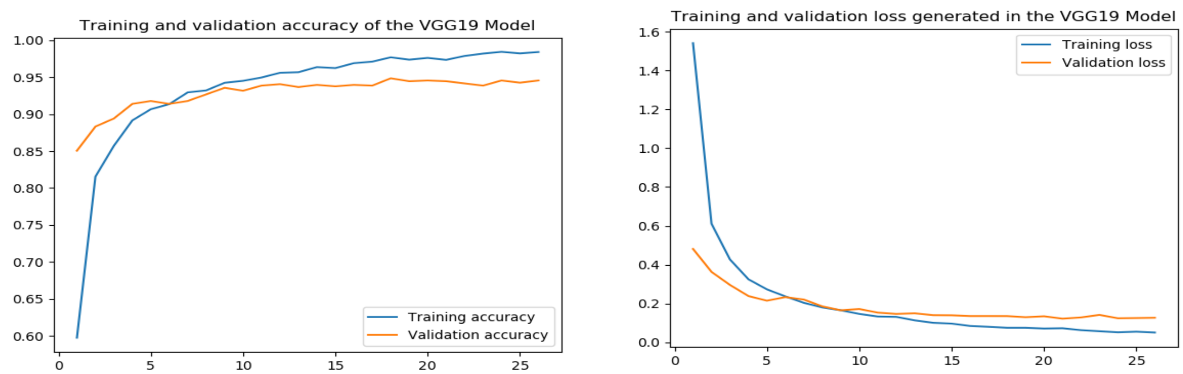


Figure 20: Training and validation accuracy and loss of VGG19

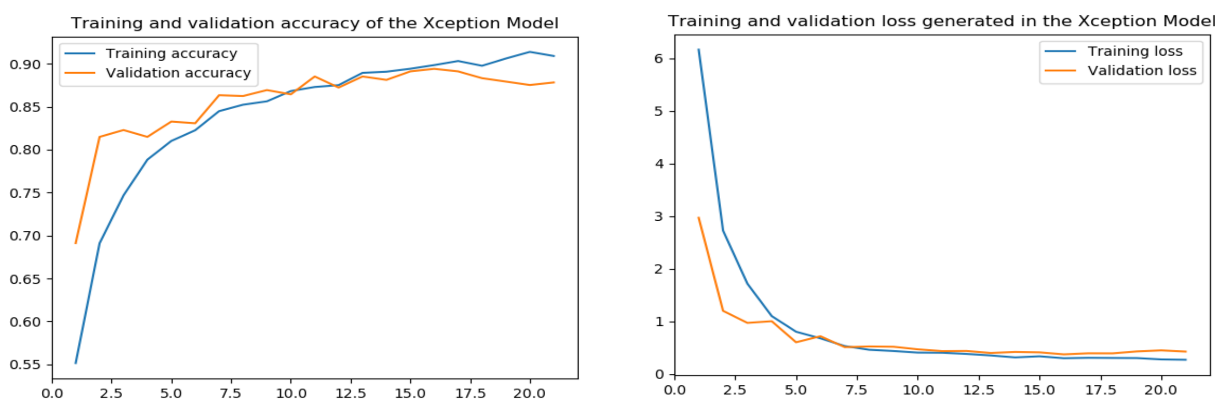
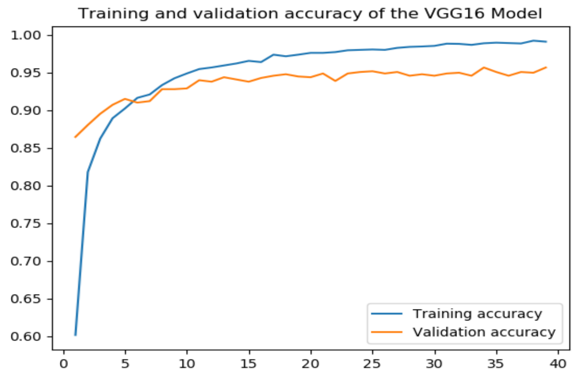


Figure 21: Training and validation accuracy and loss of Xception



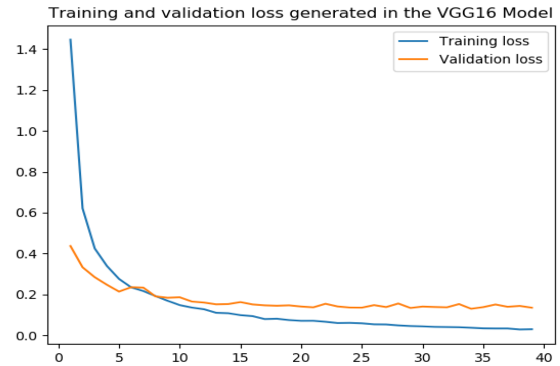


Figure 22: Training and validation accuracy and loss of VGG16

Based on the preceding graphs, it is evident that all models have attained a desirable level of accuracy. Each architecture achieved training and validation accuracies surpassing 90%, except for the Inception_V3 model which exhibited approximately 70% for both training and validation accuracies. This particular model also had the fewest number of epochs and recorded the highest training and validation losses. On the other hand, the ResNet50 architecture demonstrated the lowest error rates and the highest accuracies among the models. The VGG16 architecture necessitated the greatest number of epochs, specifically 40 epochs, before reaching the minimum point, while the Inception_V3 architecture achieved this milestone in just 14 epochs.

It is also shown the both curves for training and validation evolved the same way without great differences for all the models but Desnet201 model scored the best training and validation evolution.

3.1.2 Performances comparison

3.1.2.1 Validation accuracies

The following figure (figure22) represents the validation accuracies of different models.

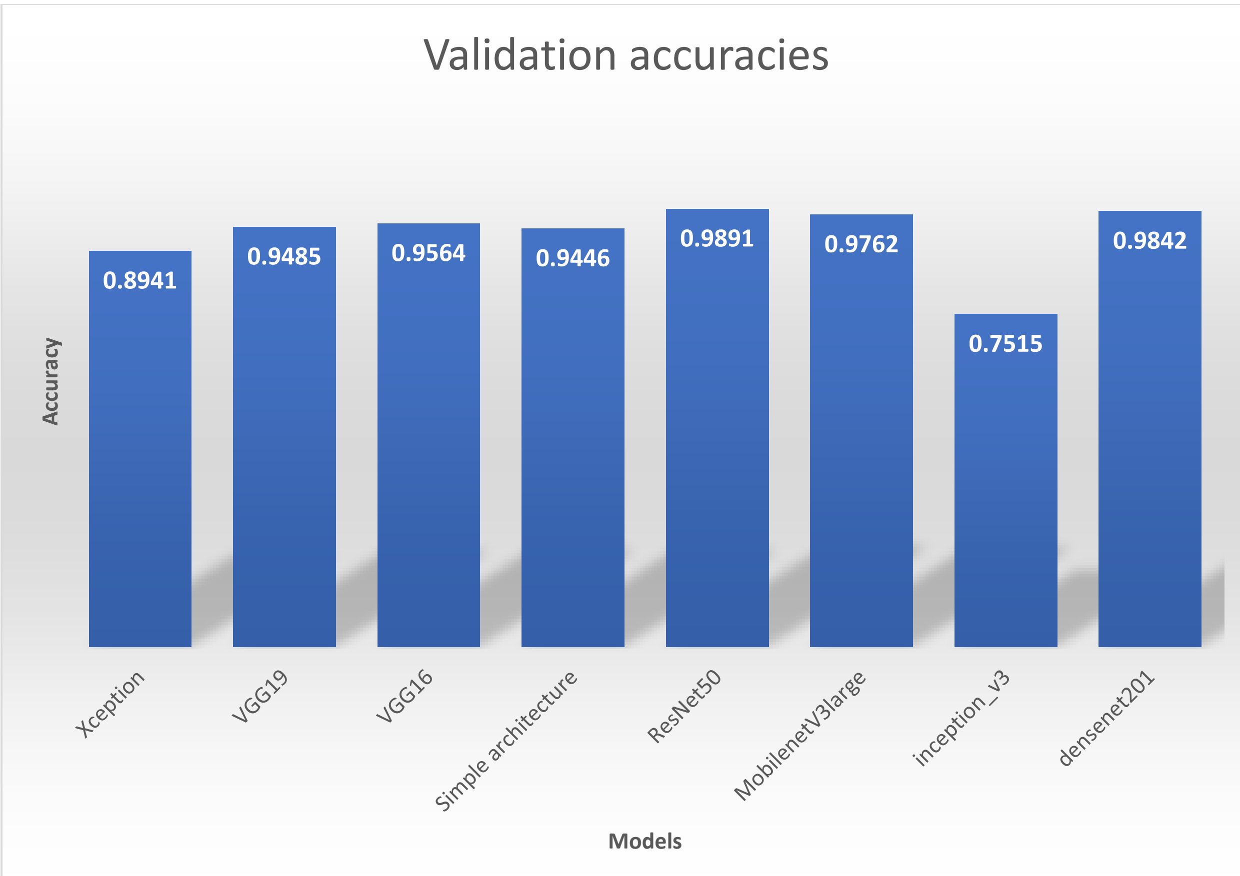


Figure 23: Validation accuracies

It can be observed that ResNet50 and Densenet201 achieved the highest validation accuracies of 98.9% and 98.4% respectively, indicating superior performance compared to the other models. On the other hand, Inception_v3 had the lowest validation accuracy which is 75.1% even though all the models have demonstrated good learning performances.

3.1.2.2 Test accuracies

The following figure shows the test accuracies recorded by each of the studied models.

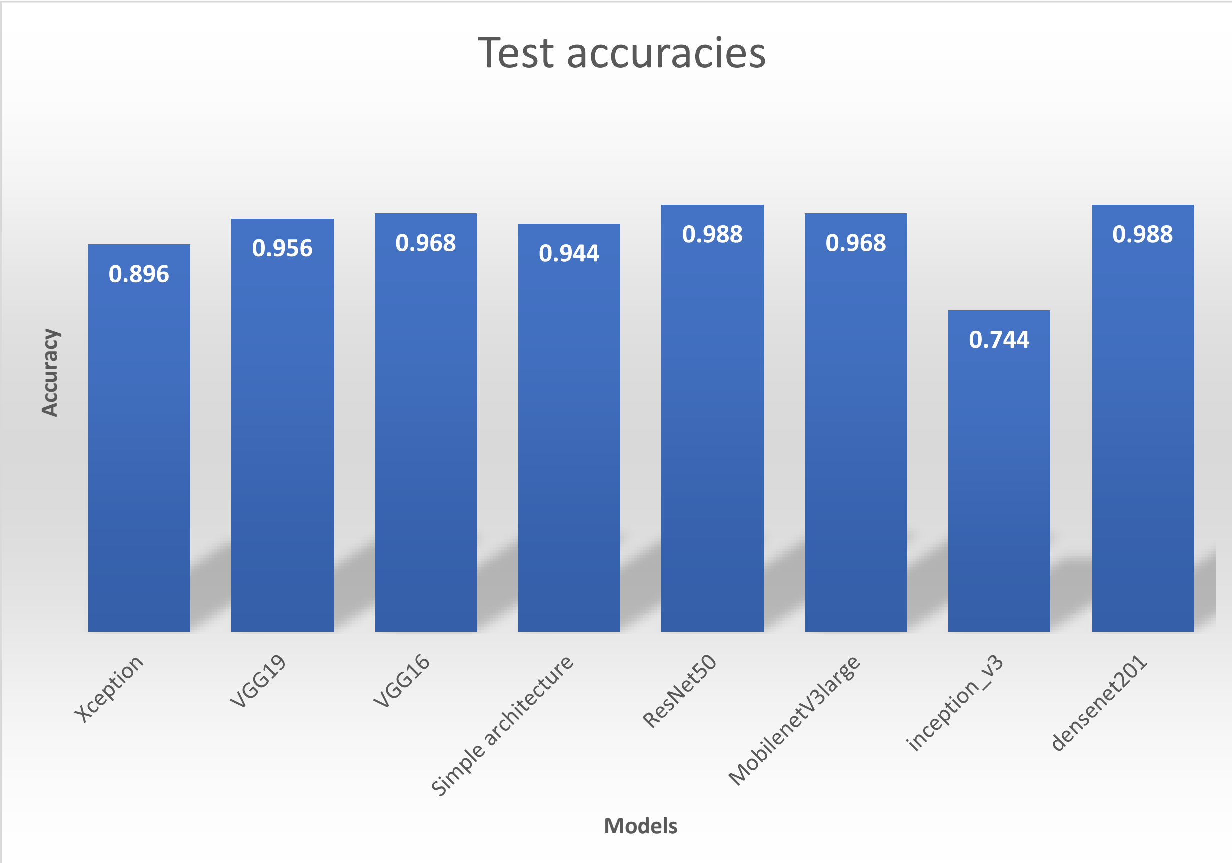


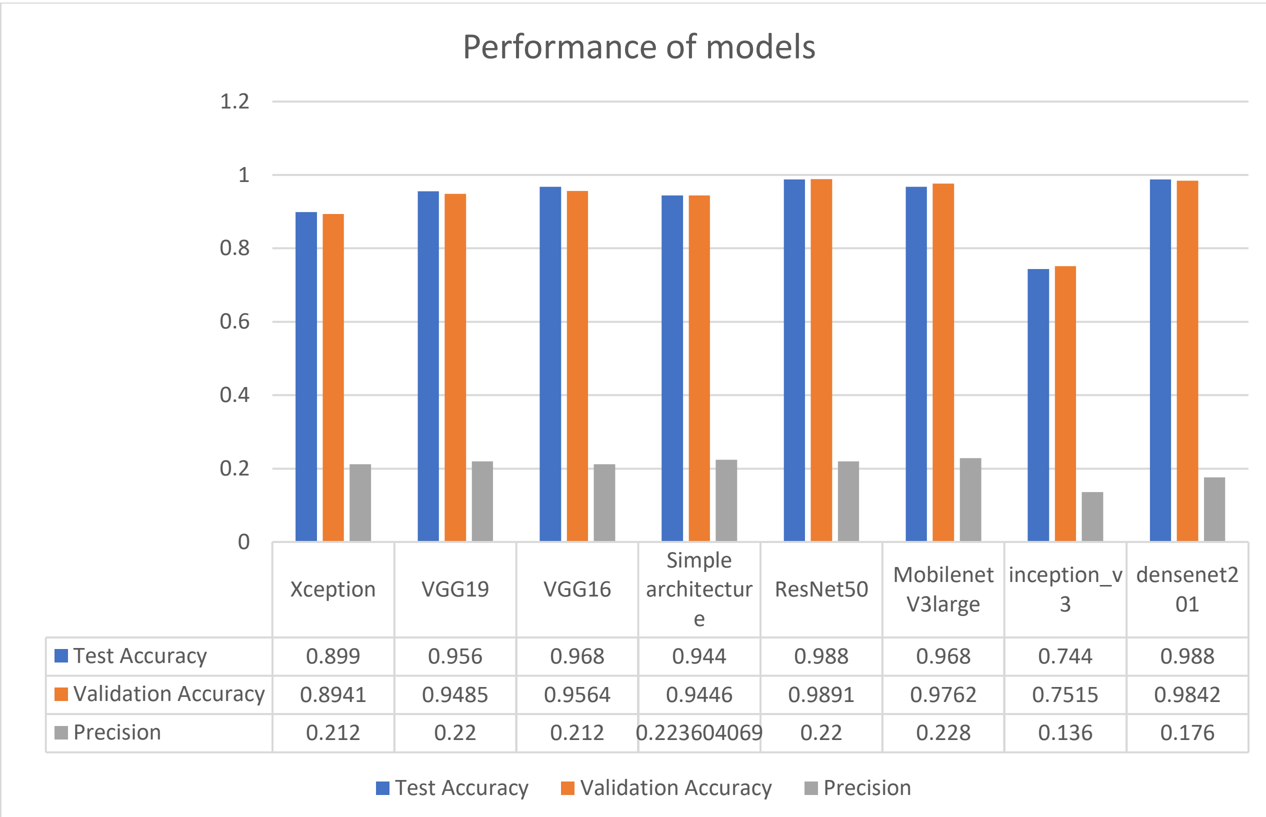
Figure 24: Test accuracies

Comparing the results of the different models, it can be observed that ResNet50 and Densenet201 achieve the highest test accuracies of 98.8% for both, indicating their strong performance in accurately classifying the test data. VGG16 and MobileNetV3large also demonstrate high accuracies, while Xception, VGG19, and Simple_architecture show slightly lower accuracies but still perform well.

On the other hand, Inception_v3 exhibits the lowest test accuracy among the models, suggesting that it may struggle with this specific classification task compared to the others.

3.1.2.3 Classification Report

The following graphs show reports of different models



	Xception	VGG19	VGG16	Simple architecture	ResNet50	Mobilenet V3large	inception_v3	densenet201
Test Accuracy	0.899	0.956	0.968	0.944	0.988	0.968	0.744	0.988
Validation Accuracy	0.8941	0.9485	0.9564	0.9446	0.9891	0.9762	0.7515	0.9842
Precision	0.212	0.22	0.212	0.223604069	0.22	0.228	0.136	0.176

Figure 25: Classification report

The figure above (figure 24) shows MobileNetV3Large and the novel architecture outperformed other models in terms of precision even though slightly higher that of ResNet50 and VGG19. But Resnet50 is still having the highest test and validation accuracies. On the other hand, it shows that Inception_V3 scored the lowest precision, recall, and f1-score. It can also be observed that all the models have the validation and test accuracies without significant different nearly the same in termers of values.

3.1.3 Application development

The following figure show the user interface.

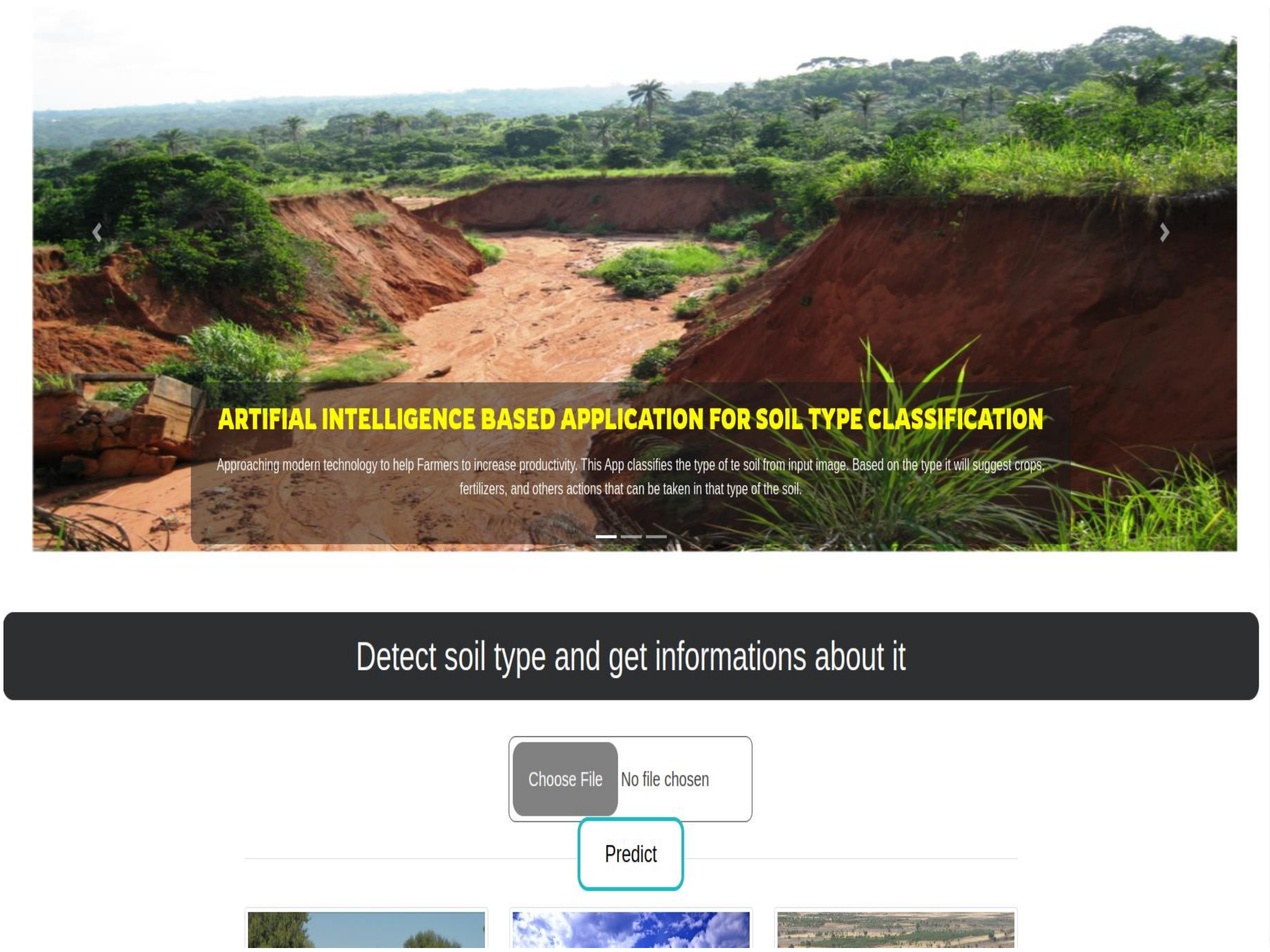


Figure 26: User interface

The use can click on the button choose file to upload the image and predict to make inference.

3.1.4 Local language integration

The Hausa language which is the language of the study area has successfully integrated in the system whereby the user can click on the button to get the informations about his specific soil type. The figure below displays a page with the button that the user can click on to Have the informations about his soil type in local Language of Maradi region.

Figure 27: Local language button

3.2 Discussion

In this study, we conducted a comprehensive performance comparison of various deep-learning models for soil classification. We compared the performance of eight models for 5 classes classification task. The results provide valuable insights into the effectiveness of different models for accurate soil classification.

Overall, all the classification models demonstrated strong performance in accurately categorizing soil types. This trend could be due to state of the surface of soil under natural conditions. The validation accuracies achieved by the models ranged from 0.751 to 0.989 for the 5 classes classification task. Similarly, the test accuracies ranged from 0.744 to 0.988 for the 5 classes classification task. These results indicate that the models were able to learn and generalize well to unseen data. This complies with the findings of Chala and Ray (Chala & Ray, 2023).

It was also noticed that there were not significant differences between the validations and testing accuracies of model. Each of the models performed almost the same way for validation and testing proving that there was no underfitting or overfitting. This might be due the usage of Kera's' call-back function for early stopping which stops the training process when there is no improvement and thus prevent overfitting and energy waste.

Among the individual models, ResNet50 consistently outperformed other models in all classification tasks. This model has been widely recognized for its effectiveness in image classification tasks and its ability to learn complex patterns and features from the data. This result aligns with that of Chatterjee et al who found that ResNet50 was the best among 6 CNN models for soil classification (Chatterjee *et al*., 2021).

The results also have shown that the model with the lowest accuracy scores was the one with smallest number of epochs. This could be due the fact that models learn progressively as time goes on.

The findings of this study have implications for soil classification in agricultural and environmental management. Accurate soil classification plays a crucial role in optimizing crop selection, soil fertility management, and sustainable land use practices. The models developed in this study can serve as valuable tools for automating the soil classification process and providing timely and accurate information to farmers, land managers, and environmental researchers.

Despite the promising results, this study has certain limitations. Only soil types used for agriculture are covered not capturing the full diversity of soil types and conditions present in the region. The performance of the models can potentially be improved by incorporating additional data sources, such as spectral information or soil composition data. Furthermore, exploring alternative architectures or fine-tuning the existing models could yield even better results.

In conclusion, this study highlights the effectiveness of deep learning models in soil classification. The models demonstrated strong performance in accurately classifying soil types, with variations observed in precision, recall, f1-score, and accuracy. The findings contribute to the field of soil classification and provide insights for further research and practical applications in agriculture and environmental management.

Conclusion and perspectives

In this research, we aimed to create, compare and select eight CNN architectures for Agricultural soil characterization and crop recommendation. We addressed the limitations of traditional soil analysis methods, which are time-consuming and expensive for farmers in the region. By leveraging deep learning techniques, specifically convolutional neural networks (CNNs), we investigated the effectiveness of different CNN architectures for soil type classification.

Through our analysis, after building and comparing the models, we found that CNNs can accurately classify agricultural soil types in Maradi, Niger. The utilization of transfer learning, which involves leveraging pre-trained CNN models, proved to enhance the accuracy of soil type classification. This finding demonstrates the potential of transfer learning in improving the efficiency and effectiveness of soil analysis techniques.

Actually, we compared several well-known CNN architectures, including VGG16, VGG19, ResNet50, InceptionV3, MobileNetV3Large, Desnsnet201, and Xception model, to determine the best-performing architecture for soil type classification in Maradi, Niger. Our results indicated that the ResNet50 architecture exhibited the highest accuracy as well as other classification, highlighting its suitability for soil classification tasks in this region.

An AI-based application was developed using the ResNet50 architecture to allow farmers to easily access and utilize the soil identification system. This application provides farmers with personalized recommendations for crops, fertilizers, and farming techniques based on the analysis of their soil type. By adopting this technology, farmers can make informed decisions, optimize their farming practices, and sustainably increase productivity.

Local language was integrated into the application to help farmers use it even if they are illiterate.

Overall, this research demonstrates the potential of AI and deep learning in revolutionizing farming practices in Maradi, Niger especially with the extension of local language. By providing accessible and efficient soil analysis solutions, we can empower farmers to overcome the challenges posed by land degradation and climate change. Additionally, the success of this research opens up opportunities for further exploration and refinement of AI-based applications in the agricultural sector.

However, while this research has made significant contributions to soil type classification using CNNs in Maradi, Niger, there are still some limits and room for several avenues for further research and improvement.

- The performance of the CNN models can be further enhanced by exploring advanced optimization techniques and hyperparameter tuning. Optimizing the learning rate, batch size, and regularization methods can potentially improve the accuracy, precision, recall, and f1-score of the models.
- The dataset used in this research can be expanded to include a wider range of soil types and regions. This would allow for more robust model training and evaluation, ensuring the applicability of the soil identification application across diverse agricultural contexts.
- Evaluating the economic and environmental impacts of adopting the AI-based soil identification application can provide valuable insights into its effectiveness and potential benefits. Assessing factors such as cost savings, yield improvement, and environmental sustainability will further support the case for the widespread adoption of such technology in the agricultural sector.
- Development of a mobile application(Android) to facilitate the use of the application.

By addressing these perspectives, future research can contribute to the continuous improvement and refinement of AI-based solutions for soil analysis and agricultural decision-making, ultimately enhancing food security, sustainable farming practices, and the well-being of farmers in Maradi, Niger, and beyond.

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Appendix

Appendix 1: Results of soil analysis

No Lab.	Identification	pH		Meq/100 g					Phosphore ppm	%				Texture %				Coordonnees	
2023/128		H2O	C.E ms/cm	CA++	Mg++	Na+	K+	CEC	Assim.	Carb.	M.O	Azote	C/N	A	L	SF	SG	Lon	Lat
129	Tsamia Koura A	4.98	0.22	3.9	2.89	0.278	0.72	7.89	36.55	0.78	1.35	0.074	11	10.38	16.51	29.04	44.07	8.07145	13.77
130	Tsamia Koura B	5.69	0.03	2.95	1.79	0.2	0.21	5.19	26.5	0.3	0.52	0.028	11	3.79	6.82	28.57	60.81		
131	Tsamia Koura C	6.1	0.07	1.95	2.01	0.157	0.046	4.22	10.27	0.12	0.21	0.025	5	0.22	3.84	25.53	70.32		
132	Sojdi A	5.98	0.13	1.95	2.02	0.174	0.102	4.25	4.53	0.24	0.41	0.028	9	0.22	9.74	18.93	71.12	7.1182	14.88
133	Sodji B	6.23	0.09	2.05	2.13	0.113	0.061	4.41	3.42	0.23	0.4	0.032	7	0.22	7.28	18.72	73.79		
134	Intouilla A	6.23	0.09	2.4	2.68	0.2	0.138	5.44	10.05	0.09	0.15	0.022	4	0.22	8.72	29.18	62.1	6.6242	14.7
135	Intouilla B	6.25	0.09	1.55	2.94	0.209	0.143	4.94	7.95	0.23	0.4	0.02	12	1.57	10.39	34.19	53.75		

136	Gounnaka A	6.32	0.13	0.195	0.852	0.113	0.061	1.24	5.3	0.18	0.31	0.017	11	0.22	4.72	28.09	67.69	8.0322	13.68
137	Gounnaka B	6.12	0.13	17.15	28.9	0.165	0.067	46.32	5.41	0.03	0.05	0.021	2	2.94	3.28	24.32	68.86		
138	Tchizon Kouregue A	5.97	0.08	9.7	1.4	0.209	0.082	11.47	4.42	0.03	0.05	0.018	2	0.72	6.58	38.12	56.02	7.40731	13.5
	Tchizon Kouregue B	6.05	0.08	12.05	3.83	0.218	0.056	16.27	9.38	0.04	0.05	0.025	2	6.08	4.44	33.93	55.54		

Appendix 2: Survey form

Nom et prenom	Sexe	Age	Type (Nom) de sol	Types de speculation cultivees	vocation des sols	Types de fertilisants

Appendix 3: Soil units of Maradi by departments

Département	Lithosols	Régosols	Sols brun rouge	Sols ferrugineux tropicaux lessivés	Sols ferrugineux tropicaux peu lessivés	Sols hydromorphes
Dakoro	0	0	4505	7963	0	2003
Mayahi	0	0	0.54	6157	0	337
Tessaoua	15	0	1190	3030	740	22
Guidan Roumdji	0	163	0	3700	624	336
Madarounfa	0	801	0	2086	151	224
Aguié	10	0	0	1855	0	145
Bermo	0	0	1915	0	0	149
Gazaoua	2	0	9	454	169	132

Source: (Moumouni, 2015)

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