Classification of Bangladeshi Soil Texture Using Convolutional Neural Network

by

Hafiz Mohiuddin Raj
18301250
Sazia Shahreen
16101247
Muntaha Binte Shah
16241006
Syed Washinur Ashraf Evan
18301056
Juhayer Abdullah
18301251

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B.Sc. in Computer Science

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Brac University
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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Hafiz Mohiuddin Raj

Hafiz Mohiuddin Raj
18301250

Sazia Shahreen

Sazia Shahreen
16101247

Muntaha Binte Shah

Muntaha Binte Shah
16241006

Syed Washinur Ashraf

Syed Washinur Ashraf Evan
18301056

Juhayer Abdullah

Juhayer Abdullah
18301251

Approval

The thesis/project titled "Classification of Bangladeshi Soil Texture Using Convolutional Neural Network"
submitted by

1. Hafiz Mohiuddin Raj(18301250)
2. Sazia Shahreen(16101247)
3. Muntaha Binte Shah(16241006)
4. Syed Washinur Ashraf Evan(18301056)
5. Juhayer Abdullah(18301251)

Of Summer, 2022 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on September 22, 2022.

Examining Committee:

Supervisor:
(Member)

Dr. Amitabha Chakrabarty
Associate Professor
Department of Computer Science and Engineering
Brac University

Thesis Coordinator:
(Member)

Dr. Md. Golam Rabiul Alam
Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi, PhD
Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Abstract

In agriculture, soil is one of the most potential output sources. That is why, if we can foresee the soil's nature and how it will turn in the future as well as it's other qualities, we may achieve adequate monitoring and sustainable agriculture field usage. We can forecast many soil textures using different CNN models by doing Soil classification. As a result, our major goal is to forecast it and utilize a Convolutional Neural Network (CNN) to do so. We have applied the VGG16, ResNet50, Inception V3, Xception, and VGG19 and these are a kind of algorithm that has the capability to organize a huge number of images of separate divisions. Additionally, in our research, another algorithm is used, which is deeply related to visionary purposes. The algorithms have played a significant role in image augmentation in our research. The input is turned into a set of filters in the hidden layers to construct feature maps in the CNN model. We have used more than 2000 soil images as our data set, which helped for the betterment of our research. Images of several soil samples are used to train and evaluate these models. We have also used more than 4096 soil images of Bangladesh, creating a new scope for our research. A machine vision system consisting of a smartphone camera with an external lens, elimination chamber, USB connection, and a laptop for algorithm processing activities will be used to prepare the data. In general, the current research was carried out with five goals in mind which will be discussed in further depth in the following sections. On photos of different soil samples, these models were trained and tested. With the best accuracy percentage, the suggested models could predict soil pictures. More than 90% of accuracy from each model has been obtained, except for Xception model, where we get an accuracy of 85%. In the end, this approach will be less costly and a waste of time alternative to experimental methods for classifying the kind of soil textures on a broad scale.

Keywords: Soil texture;Predictions; CNN; Machine Learning; NN models; Ensemble; Image augmentation; Soil Classification.

Dedication

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption. The report is dedicated to our parents. We would not have made it this far without their involvement, focus, and support. We owe them a duty of gratitude. Thanks a lot to them.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ϵ Epsilon

υ Upsilon

ADO Authorized Department Officer

$AISQI$ Artificially Intelligent Soil Quality Index

ANN Artificial Neural Network

AUC Ammonium Uranyl Carbonate

BCP Biodiesel co-product

BD Bangladesh

$BoVW$ Bag-of-Visual Words

BP Building Planning

BRT Boosted Regression Trees

CNN Convolutional Neural Network

CR Continuum Removal

DIP Dissolved Phosphate

DL Deep Learning

$DRIFT$ Diffuse Reflectance Infrared Fourier Transform Spectroscopy

EC Electrical Conductivity

FC Fully Connected

$GCLM$ Ground Launched Cruise Missile

GIS Geographic Information System

GPS Global Positioning System

IDL Instrument Detection Limit

$IncMSE$ Increase in Mean Square Error

IOT Internet of Things

MAE Microwave Assisted Extraction

MBL Memory-Based-Learning

MIA Multivariate Image Analysis

$MODIS$ Moderate Resolution Imaging Spectroradiometer

MSE Mean Square Error

$NIST$ National Institutes of Standards and Technology

$ODBC$ Open Database Connectivity

PCA Principal Component Analysis

PLS Partial Least Squares

$PLSR$ Partial Least-Squares Regression

$pXRF$ portable X-ray Fluorescence

$ResNet$ Residual Network

RF Random Forest

RGB Red Green Blue

$RMSE$ Root-Mean-Square-Error

ROC Regenerative Organic Certified

SAR Sodium Absorption Ratio

$SIFT - BoVW$ Scan Investigate Filter Target- Bag-of-Visual Words

SOM Soil Organic Matter

$SPSS$ Statistical Package for Social Science

SVM Soil and Vegetation Map

$SVMR$ Support Vector Machine Regression

TDR Time Domain Reflectometry

USB Universal Serial Bus

$VGG16$ Visual Geometry Group

$VNIR/SWIR$ Visible near-infrared/ Shortwave near-infrared

WSA Water Stable Aggregates

Chapter 1

Introduction

In the sphere of agriculture, new technology and innovations have resulted in considerable, advancements. As we know that the basic component of terrestrial ecosystems is soil, and soil degradation reduces the soil's capacity to offer ecosystem services. Moreover, Pedotransfer functions (PTFs) have been utilized to forecast a variety of soil attributes throughout the last several decades[1]. On the other hand, a greater knowledge of the soil at progressively smaller sizes is required to achieve agriculture and environmental management that is sustainable but soil sampling and laboratory tests are time-consuming and costly and they cannot effectively offer this information [2]. Texture, which is one of the most fundamental characteristics, has a significant impact on the physical, chemical, and biological aspects of soil. As a result, soil texture is linked with plant water, nutrition, air, and temperature demands, resulting in good crop yields [3]. Soil texture is an essential physical property of soil that influences a wide range of soil functions, including water retention and fertility. That is why soil texture has greatly impact on calcification, fertilization, erosion management, and irrigation[4]. By using the right quantity of variables we can be able to maintain lower costs and reduce groundwater contamination from herbicides, pesticides, and fertilizers, eventually increasing crop production. We can be able to maintain the soil quality in every single sector of soil components if we can predict the accurate condition of soil textures. Many novel methodologies and concepts for forecasting soil qualities in unvisited locations based on existing documented data have shown to be promising and successful. Digital soil mapping, for example, has been widely recognized as an effective method for inferring soil patterns across multiple geographical and temporal dimensions, thanks to improvements in computer science, distant and proximal sensing [5]. Taking point samples systematically or randomly to obtain soil data, including soil texture, is another example of doing a field soil survey. In order to create soil maps, data is often interpolated from point samples. Kriging is one of a variety of interpolation methods used to create soil maps[6]. Because traditional soil texture prediction methods are costing a lot of money, time, and requiring a lot of expensive, non-portable, and intricate equipment, chemicals, and specialists, this study used a machine vision system and a modified convolutional neural network algorithm, as well as hardware, to predict soil samples based on their image texture. In general, the current study was conducted with a set of goals or objectives in mind. Using a machine vision system to create a deep learning model and compute the rapid and accurate prediction of soil textures classification. This is the study's main goal or purpose, which will be covered briefly in the next section. A soil map at a large scale requires a large number of sampling points because soil characteristics vary widely spatially. A number of geostatistical models have also been developed to predict soil texture distributions across regions and to investigate how soil texture relates to the environment[7]. Digitally created soil section photos utilizing standard cameras, microscopes, or examined under separate radiance reveal a wide range of geometrical characteristics. Soil categorization might begin with an understanding of soils as an asset and a substance [8]. Idiomatic expression induction is a technology used to determine soil salinity that was initially created for the oil business for well logging. It has been used in soil research for 25 years[9]. Deep learning (DL) research has recently yielded exceptionally promising classification results in a variety of applications, including image identification, natural language processing, and speech recognition[10]. According to [11], soil moisture has a crucial function in the water cycle of soil-plant-atmosphere, not only in maintaining plant development but also in the condition of the water cycle

1.1 Research Problem

The current study was conducted to evaluate the soils of Hyderabad, Telangana, in order to assess their land capacity, irrigability, and suitability for various crops, as well as to examine the area's soil fertility restrictions, according to [12]. Hyderabad was founded on the Musi River's banks and it has developed on both sides of the river throughout the years. The river has become a rubbish dumping ground due to unplanned development and a lack of management. All untreated household and industrial waste fluids that are released. As a result, it has become polluted beyond the city limits of Hyderabad. Efforts to sanitize it have proven fruitless. A lake that was made by humans, sometimes known as HussainSagar Lake, separates the two cities. As we learned from the examples above, the varied colors and textures of soil images are often determined by their diverse local components [13]. It showed us how to categorize photos of soil based on it's texture and color. The form of soil particles and topography have not been as efficient as they may have been due to the inherent variety in soil appearance. Soil categorization may be limited by the typical SIFT-BoVW technique, which does not include any color or texture information in the picture description. Because soil texture is difficult to evaluate directly, a technique for evaluating soil texture based on elements that are strongly connected to soil texture is outlined [3]. The soil EC sensor as well as industrial sensors, were employed in the agricultural investigation. The needed input parameters are gathered using the camera: soil EC and texture characteristics are extracted from the soil surface picture, respectively, and the target field's soil texture information is obtained using the prediction model. According to [14], for modeling and validation, soil data was separated into sub-datasets, 70% and 30% of the total samples were found in each, respectively. In SGLMs, the least important model change variables are eliminated using a step function based on Akaike's information criterion, and a final regression model is constructed. The larger the prediction error when one variable is removed from the model while others are retained, the more significant it is. The percentage of mean square error increase is one of the metrics supplied by the RF algorithm. The IncMSE statistic is a reliable and effective technique for determining the relative importance of each independent variable as well as preventing bias. During RF modeling, one variable is permuted while the others are preserved in trees, resulting in a percentage increase in mean square error (MSE) of predictions (calculated with out-of-bag cross validation). Weed infestation, plant diseases, and pesticide resistance are all important challenges to agricultural productivity [10]. Data of moisture were analyzed using SPSS and found to be non-stationary, showing that the water content is impacted by other climatic factors. The melting of soil texture water is accelerated by increases in the environment which indicate negative variables [11]. Soil mapping is a difficult undertaking, and in this case, the geophysical approach wins out for this scale of watershed [9].

1.2 Research Objectives

Based on a modified convolutional neural network, a machine vision system, for a fast and precise soil texture prediction, an automated monitoring system is used.
1) In order to create a deep learning model along with a machine vision system, we have to identify soil texture photos.
2) Assess the suggested model's influence on height.
3) Examine the picture preparation processes used by the suggested model.
4) Develop a user-friendly graphical user interface for soil type forecasting.
5) Implementation of models to anticipate the soil texture with the greatest accuracy.
In the next sections, we will go through these goals in further detail.

1.3 Thesis Structure

In chapter 1, we discussed the Research Problem and Research Objectives. In chapter 2, we discussed Literature Review, Predict Software, Automation,Related Works. In chapter 3, we discussed Methodology and Proposed Models. In chapter 4, we discussed Data set and Image Augmentation. In chapter 5, we discussed Implementation and Results. In chapter 6, we discussed the Conclusion and Future work.

Chapter 2

Background Study

2.1 Literature Review

Prediction software has made it easier for various industries to make quick and accurate decisions even without the existence of direct data sets or in cases where collecting a large decisive data set is either too time-consuming expensive due to natural barriers or local lack of knowledge and budgeting. Using data collected from one part of the world or event and scaling them to suit the changes of conditions of the target event, can now easily predict or analyze the desired output in our thesis; we aim to predict soil texture by taking in data from images and using deep learning and information collected from previous works. This is especially suitable in Bangladesh, where data is limited and the technological budget prevents exploration.

2.2 Prediction Software

Various research papers have tested the accuracy of such, predictions including comparing different techniques. According to research paper [1], a comparison was done between GLM algorithm and ANN each in terms of the RMSE, and MAE in the cross validation procedure. The GLM gave training and testing, respectively. According to paper [2], Memory-Based Learning (MBL) uses the concept of human reasoning when a new analysis is needed, similar samples are recalled from memory and those data sets are combined to find a solution to the new problem. This paper presents an alternative to ANN and SVMR which need complex fitting. Mapping of the soil is done using VNIR/SWIR that allows us to do soil spectral analysis to obtain data sets. In paper [12], a model to classify soil textures that uses linear discriminant analysis(LDA) was built. Recording of soil properties such as pH, moisture, temperature, organic carbon, nitrogen, phosphorus and potassium were taken to be independent variables while soil type is the dependent variable. The selection of variables and features was performed using the Boruta algorithm. In paper [15], Amount Forecasting Advantages ,Draught Monitoring via both artificial and automatic observational soil moisture data, acquired through transmission technology of the internet of things are discussed. The paper also mentions drought forecasting and irrigation amount forecasting. According to paper[16], Machine Learning techniques are used to develop a soil quality index and artificial intelligence soil quality index which reduces costs of local farming problems [5], assuming that the soil texture is relatively homogeneous. Environmental conditions (e.g. on a regional scale) are strongly correlated with soil chemistry and therefore, it can be predicted from the direct basic measurements of PXRF. RMSE values are significantly lower than those reported in previous studies using other proximal sensors techniques. In paper [17], this article introduces MIA-based green analysis methods . MIA model that uses PLS to generate digitally processed soil images and particle size content can be used for computer vision recognition of classification of soil structure. Data can be processed in real-time and an onboard computer that does not require the use of a microscope. In paper [18], the study compares the results of two different approaches for estimating soil texture using VNIR SWIR reflectance measurements .In this paper the PLSR strategy outperformed the CR approach in predicting soil textures and content. According to paper [6], the ratio of sand , clay and silt were measured using course resolution images and then converted to a better resolution using Digital Elevation model(DEM) then input as nodes into ANN. Paper [4], compares the support vector machines with ANN and classification tree strategies where the former technique showed better results than the later Paper [13], explains use of smart phone captured images processed in python 3.6 environment. The dataset was used to train Convoluted neural network and random forest algorithm to predict the content of the soil . Paper [3], the vehicle-mounted detector is used to take in input from which the texture is analyzed using EC sensor and a model is created from images and sensor information and input into a prediction software. This technique is used in farmlands. Paper [19], uses attributes of plants and vegetation in the region to predict soil properties using Sentinel1 data and models it with time-series SAR information. In another research they used satellite remote sensing for monitoring soil texture which provides a regular basis up to date [20]. A study also showed how to predict soil texture distributions by applying ANN models for high-resolution depth-specific soil texture distribution in some rural areas of China [21]. In another study they used image processing and computer vision techniques to classify the soil texture and then they applied deep learning and machine learning algorithms to soil texture classification approaches like CNN model [8]. Also for predicting the soil texture moisture of different types of soil input machine learning methods can be used as per a research described broadly in their paper [22].

2.3 Automation

Automation Paper[23], automation practices, includes internet of things and wireless technology. From the above discussion, we surmise that by studying the techniques used we will be able to put together a portable device that takes low resolution pictures of soil in Bangladesh and compare and process the picture with the selected data sets. Using the prediction software best suited and most accurate for the situation we may be able to predict the texture of the soil in the picture and accurately deduce and produce a soil map or a functional list of characteristics that will be helpful to the user. Moreover, a study showed a unique technique of using the deep learning method to predict the soil organic carbon content by using satellite based variables[21]. For getting more accurate predictions on soil mapping, deep learning methods are showing us great potential[24].

2.4 Related Works

In this discussion we can provide a review of previous relevant works in accurate prediction of soil texture in the context of using some algorithms and methods. We examine the various methodologies utilized to obtain the basic results, as well as how the soil texture prediction system is widely used and its own set of obstacles. There are many kinds of textures in soil for example water, density, pH soil erosion potential etc. There have been many laboratory methods developed, like Continuum Removal (CR) and Partial Least-Squares Regression (PLSR). They can relate the soil spectrum to soil attributes. Then, with the help of Deep learning and computer vision, researchers have been studying soil texture features by using microscopic image analysis. Moreover, one of the known algorithms like the BoVW algorithm has been used for a long time to determine soil surface characteristics like color and roughness which were then tied in with sand, silt, and clay with the help of PLSR. Further, for evaluating soil morphology, a mobile-phone with decent image acquisition capabilities can be useful. Furthermore, Random Forest (RF) is a great technique that determines a sample using hundreds of decision trees. In terms of prediction, researchers came with a decision that the RF ensemble outperformed a single tree. From the above part, we can see that in most of the research, they had a target to create a revolutionary and cheap setup comprising a mobile-phone, a modified dark chamber and an android application to predict the soil texture using different types of samples in the laboratory with the help of RF and CNN algorithms. Also ANN models can be used to classify the soil texture in different order. Another method Transfer learning is used for classification of soil in another paper which is very impressive for getting the results[25]. Moreover, another study of deep learning showed the prediction of soil moisture which ensures decent accuracy in predicting the direction and values of soil moisture data [11]. The research study focuses on geographical distribution and various soil textures in Pingdu city, which is an area of warm climate with different flavors of weather as stated in paper [26]. Accomplishing textural examination, Pipette method is used which is considered as one of the quality techniques. Along with this, RGB color replicas were also used for exemplification of soils with the help of computerized image preparing [27]. There is an indication about categorization of soil texture and to do this a vector support machine is used and that is straightforward and this method is also used for binary categorization of soil [28]. For minimizing the cost and for different size of exaggeration, specifically microscope is picked and there is a demonstration about the connection between the image parameters and logarithm [26]. The study reflects about the evaluation about numerous qualities of soil, their difference their and spatial and temporal variety and a method which is related to extraction that involves acid is used for numerical description and result of this is used to determine various functionalities [29]. Different proximal sensors strategies are employed to forecast the correct soil qualities [30]. Moreover, variables also played an important role for the purpose of accurate prediction [30]. For examining the soil specimens, a hydrometer method combining with another method is used [30]. Various samples of soil are taken from the 11 countries to enhance the research purpose and to get a better result and also compares between two of the most important dimensions of the texture known as LDA and MIRS [31]. Specifically, a CNN model is chosen and one of the most vital focal points is visualization of data and to do that deep learning plays a very significant role and visualization is also very much needed unrefined data [32]. The study distinct on different dimensions of feature of soil like- equilibrium of the carbon, reducing global warming and so on and for these types of features deep learning models are applied and in this case some restrictions are discovered but in the upcoming days there is a huge possibility to overcome the restrictions [33]. These are the related works which have been already done by the other researchers.

Summary of the paper regarding Soil Texture Prediction :

Ref	Task	Classifier	Database	Accuracy
[1]	Using easily know variables, forecast soil aggregate stability	ANN,GLM, RMSE,MAE	9 among 12 were found of USDA soi Texture	According to the study,WSA estimates with an r^2 = 0.27.
[2]	Forcast of soil Diffuse Reflectance Spectra	VNIR, PLSR; SVMR; BRT	Soil samples of Czech Republic	NA
[12]	Soil texture classification	Linear Discriminant Analysis (LDA)	Hyderabad soil samples	Accuracy=0.963 Classification of the fraction:((TP+FN)/ (TP+FP+TN+FN))
[15]	Agricultural Drought Monitoring and Forecasting using an Integrated Service System	MODIS,GIS, IDL,COM	ADO and ODBC	NA
[16]	Soil quality and health indices using Artificial Intelligence	AI,Artificially Intelligent Soil Quality Index (AISQI)	MetaData	Different models could be refined having the same index in order to improve accuracy
[23]	Comprehensive review on automation and agriculture	FL, ANN NFL, ES	ZigBee Server	NA
[5]	Characterizing of soils	PXRF,NIST, GPS	Louisiana and Capulin datasets	Determines positive linear relationship(R^2= 0.94)
[17]	Prediction of soil texture using image analysis	MIA,DIP,PCA, PLS,NIR,DRIFT	Mean-centered dataset	NA
[18]	Prediction of soil texture	VNIR-SWIR, ASD,RMSE, PLSR,CR	Three specific agricultural areas	Fraction of clay: (RMSE=5.8%, R2 =0.87)

Table 2.1: Summary of table the paper regarding Soil Texture Prediction I

Ref	Task	Classifier	Database	Accuracy
[6]	Prediction for soil texture	ANN , DEM	Black Brook Watershed (BBW)	Clay content=88% Sand content=81%
[4]	Identification of soil texture using comparison between ANN and support vector machines	SVM-poly,AUC,ROC	Use three sets of soil data	SVM-poly=0.944 clay=0.794 loam=0.992 sand=0.661
[14]	Prediction of soil fertility and texture through pXRF	BCP,SGLM,RF	Randomly divided into three sets	Xujiahe 0.954 Daye 0.933
[13]	Predicting soil texture through smartphone captured digital images	RF,CNN,SOM	90 soil samples	clay = 32.08% Sand=6.31% Clay=6.23%
[3]	Vehicle-Mounted Soil	GLCM,EC,GPS	Soil data set	Accuracy = 84.86%
[19]	Soil prediction using time-series Sentinel-1	SAR,SNAP,GRD VH,VV	P band and L-band SAR	Mean RDP=0.99
[20]	Wheat yield prediction using Deep learning,ML,GEE	DL, DNN, LSTM,GEE	NA	NA
[21]	Prediction of depth-specific soil	ANN	385 soil profiles	NA
[7]	Prediction by DL	MODIS MCD12Q2,CNN	NA	Accuracy of CNN= 5.57% of RMSE and 31.29% of R^2
[24]	Mapping of soil	DSM,CNN	NA	NA
[8]	Soil classified by CMV	ANN,RGB,HSV CNN	'Database acquisition device' points out to the appliance.	For classification, accuracy rate=95%
[22]	Prediction of soil moisture constants via machine learning methods	kNN,ANN,FC, PWP,PTF	The training and testing data were distributed in an uneven manner.	Best accuracy was achieved during RRMSE10
[9]	For soil and water holding capacity	RME,EMI,ET	Semivariogram modeling is used	NA
[10]	Detection of Crops and Weeds with Similar Morphologies	4 models of CNN	3 comparison experiments was used to find the value.	Accuracy was 98.60%
[11]	Soil moisture	DL,BP,TDR	The correlation of the soil moisture dataset.	Accuracy found 15.77% and 15.26%

Table 2.2: Summary table of the paper regarding Soil Texture Prediction II

Ref	Task	Classifier	Database	Accuracy
[25]	Soil texture images	ResNet50, TL, VGG16	1.2 millions dataset of RGB images with 1k classes	Accuracy for prediction is 78.1%
[34]	Examine textures of soil	Kriging, Cokriging	58 specimens from Pingdu city	Kriging highest value=58.3, cokriging highest value =65.9
[27]	Textural evaluation	LSSVMR, PLS, SPA-MLR	177 different dirt samples from the top 10 cm of the ground of Brazil.	Above 90%(LSSVMR)
[28]	Predicting categories of soil	Lin-SVM	216 specimen soil	Mean precision is 0.5. and average kappa is 0.31.
[26]	Picture evaluation	Masking algorithm	56 various areas	Span of colors 0.12 to 0.23
[29]	Removing sulfuric acid	N/A	74 locations near expressway	Removal rate 36 %
[35]	Soil surface identification	RF	236 soil types are collected from research region	Changeability percentage 53
[30]	Analysis of layered materials	PLSR	Specimen of 432 soils from countryside of Denmark	0.028 to 0.426
[31]	Measurement of soil quality	LDA, MIRS	Various types of soil from Europe	Gault percentage more than 60
[32]	Estimating soil characteristics	CNN	Different random soil samples	0.63 to 0.94

Table 2.3: Summary table of the paper regarding Soil Texture Prediction III

Chapter 3

Methodology

In this section we will explain how we acquired our dataset on which we performed image classification. From Kaggle.com and Shutterstock images, we acquired four classes of soil image data. The suggested methodology entails the collection of datasets, CNN model training, classification of test images, and results. The dataset needed to be divided into training and the models are assessed. We split into train, test format in 80:20 ratio respectively. 2614 images were divided into 2264 train sets and 350 test sets. This data set we called as Random data set of soil texture pictures of different sides of the world. After that, we have collected soil texture pictures of Bangladesh. 4879 images were divided into 4089 train sets and 790 test sets of Bangladesh soil pictures. Also, here we splited the dataset 80:20 ratio.

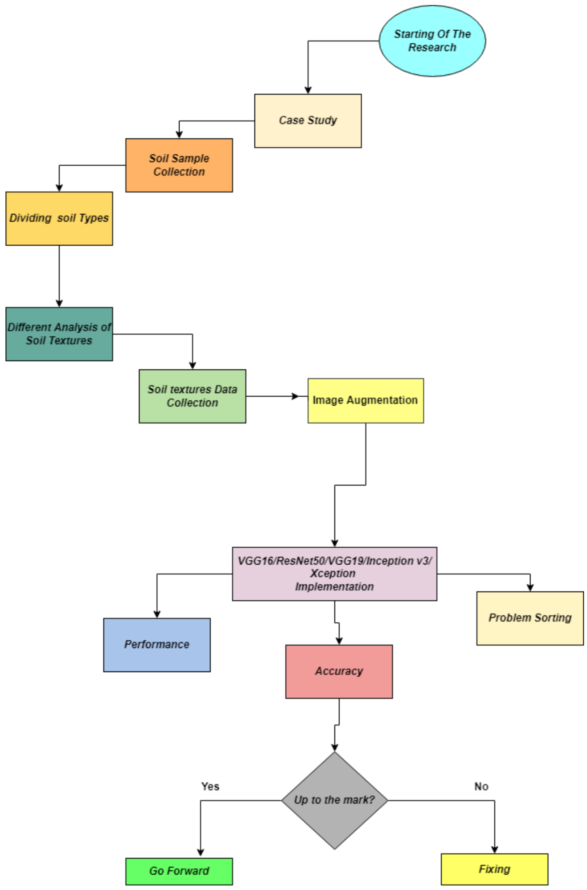


Figure 3.1: The flow chart of the proposed prediction model

3.1 Implemented Models

As we chose CNN for examining the data and got the accuracy, so we had to take few models of CNN. We used 5 models of CNN(Convolutional Neural Network) to perform image classification on our data, namely Vgg16, ResNet50, Vgg19, Inception V3 and Xception. We made an effort to compare the outcomes in different ways and in different stage. The models we used are described in more details below.

3.2 Convolutional Neural Network [36]

It is frequently utilized in image training, recognition, and prediction in technologies such as self-driving vehicles and facial recognition. It is a sort of artificial neural network fashioned after the neural functioning of the human brain. Convolution is a mathematical word that describes the process of multiplying two functions or matrices to produce another matrix in order to extract certain properties from the two prior functions. Convolution, pooling, and completely linked layers are all possibilities. The input is an image. The first layer that extracts features from an input picture is convolution. The pooling layer reduces the number of layers to the most important, lowering expenses. The fully connected (FC) layer identifies the item in the output layer by determining it from pixels. The Convolution layer, FC and pooling stacked together form the architecture of CNN.

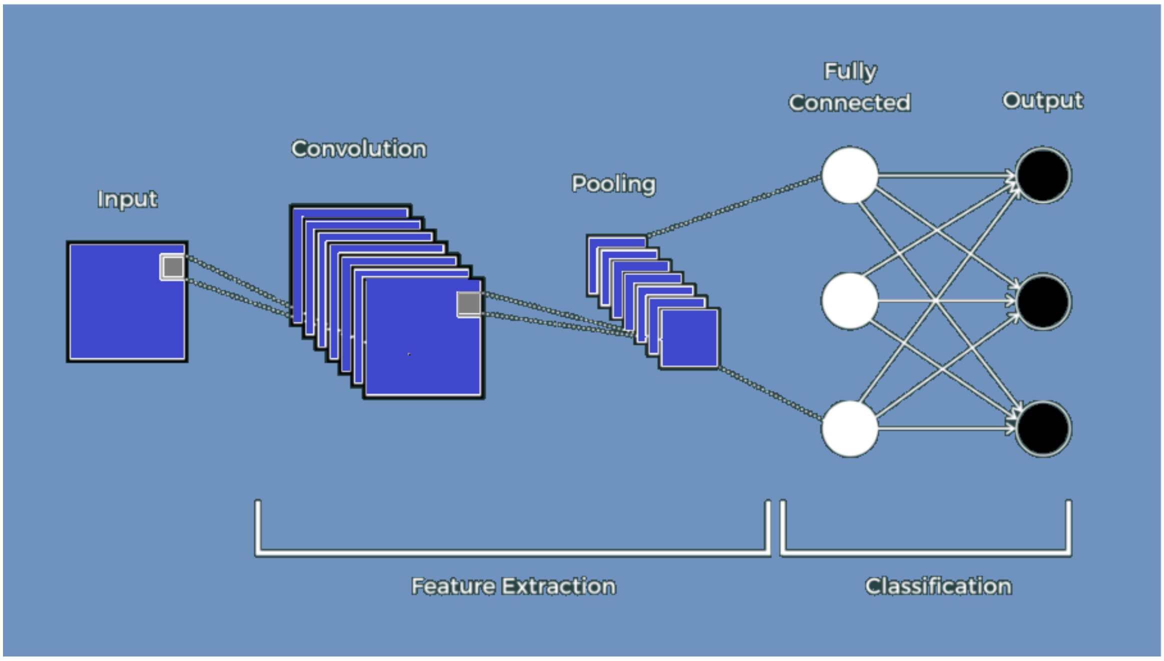


Figure 3.2: CNN Model Architecture [36]

Specific attributes of the code: The rarget sizes of these images are all 224*224 and class mode is set to categorical cross entropy and the loss function of the compile function is also set to categorical cross entropy and the metrics monitored is set to "accuracy"

3.2.1 VGG16[37]

One of the models we have employed is the VGG16. This model is distinct since it continuously uses 3 x 3 filters. Two consecutive 3 x 3 filters have an effective receptive field of 5 x 5, whereas three 3 x 3 filters have an effective receptive field of 7 x 7. In this way, the sum of multiple 3 x 3
In place of a larger receptive area, filters can be used. In addition to the three convolution layers, there
The decision functions are also improved using nonlinear activation layers. Included in the weight parameters are
In the pre-processing stage, we normalize the RGB values of the image (3 * 32 C2 = 27 C2).
Before Relu activations, the image passes through the first two layers with a 3x3 receptive size.
to keep the spatial resolution intact. The activation maps are then subjected to the spatial max filter.
pooling across a 2 × 2 pixel area with a 2 pixel stride.

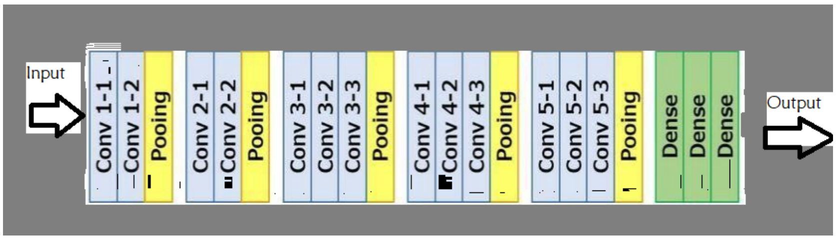


Figure 3.3: VGG16 Pooling Models[37]

At the end of the first stack, there are activations totaling 112 by 112 by 64. When the second stack includes 128 filters, the stack is 56 x 56 x 128. The third stack is composed of three convolutional layers and a max pool layer. The stack's output is 256 by 256 by 28. Then, two stacks of three convolutional layers are built, each with 512 filters. The ultimate outputs of both of these stacks will be 7 7 x 512. Three FC layers are then added after flattening the convolutional layer stacks. With 1,000 neurons, the last FC acts as the output layer and represents the 1,000 potential classes in the ImageNet dataset. Each of the first two FC has 4096 neurons. The Softmax activation layer is then used for category classification.
Specific attributes of the code: 13 convolutional layers with ReLu(Rectified Linear Unit) Activations. 2 Dense Layers with weights 256 and 128 respectively, followed by a Dense Layer that specifies the number of class and implements Sigmoid Activation. On the results we use SGD(Stochastic Gradient Descent) Optimizer with a learning rate of 0.0001. The model is fitted with an early stopping with patience of 20. We run it for 50 epochs.

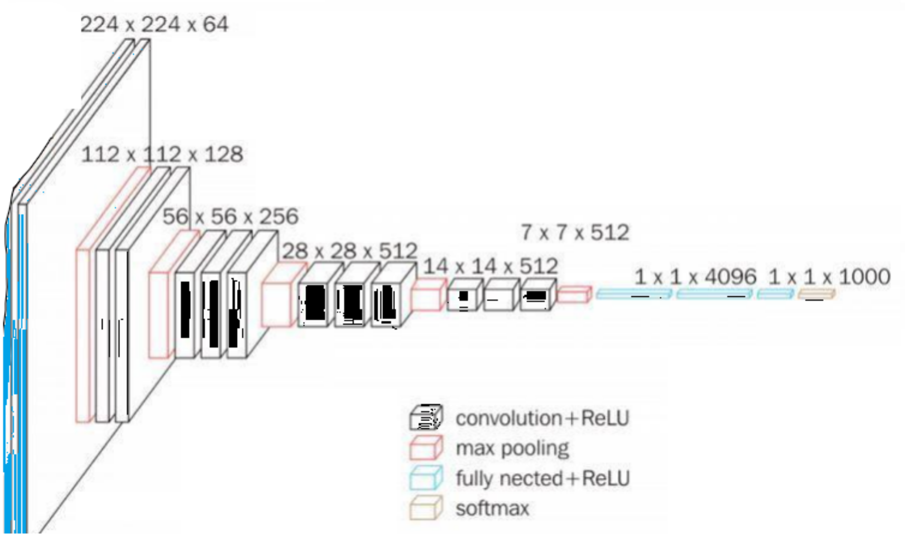


Figure 3.4: VGG16 Model Architecture [37]

3.2.2 ResNet50[38]

We have employed Keras and the Residual Network or ResNet50 model to categorize our dataset. This model provides more accuracy than the majority of models, including vgg16, and addresses the vanishing gradient issue. It is made up of leftover blocks, as shown in the second image below. It has a function called "skip connection" that enables it to skip a few levels by adding the initial input to the output of the residual block. The mathematical expression explains it:

$$H(y) = f(ay + c)$$

$$H(y) = f(y) \tag{3.1}$$

After skip function:

$$H(y) = f(y) + y \tag{3.2}$$

Extra zero entries pad the skip connections. Projection method is used to match the dimension , adds 1×1 convolutional layers to input, making the resulting function:

$$H(y) = f(y) + a \cdot 1y \tag{3.3}$$

These links also help to ensure that the top layer performs at least as well as the bottom layer and not worse by allowing the model to learn identity functions. There are five stages, each of which has a convolution and an identity block, to further clarify. There are three convolution layers in each identity block and convolution block. The ResNet-50 has over 23 million trainable parameters. the ResNet-50, trained with Keras. It makes use of a VGG-19-like 34-layer simple network design

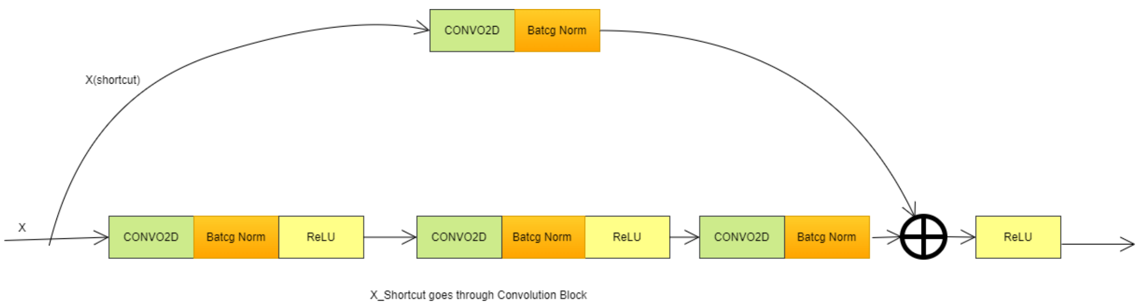


Figure 3.5: ResNet50 X ShortCut [38]

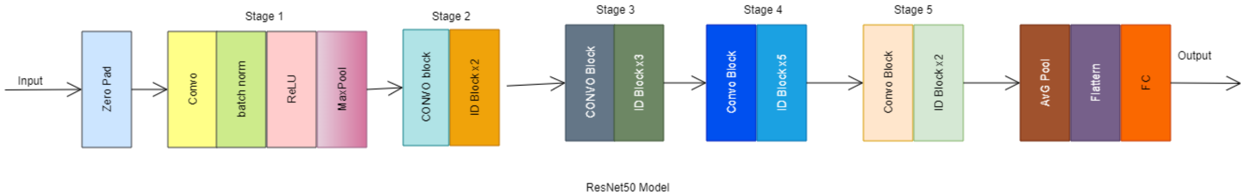


Figure 3.6: ResNet50 Model Architecture [38]

and has the skip connection functionality. These shortcut links later convert the architecture into the residual network.
Specific attributes of the code: Convolutional layers added with stride=1 each and average pooling done toward the end. Then it undergoes a dense layer of weight 256 and 128 respectively with ReLu activation followed by another with sigmoid activation. Model compiled with early stopping with patience of 20, run for 50 epochs. The optimizer used is SGD with a learning rate of 0.001.

3.2.3 VGG19 [39]

VGG19 stands out among so many Convolutional Neural Networks. It contains 19 layers. There are different versions of VGG19 like-VGG11, VGG16 and so on. VGG is utilized for picture classification and in addition, it gives the advantage to work with more than one million photos. Basically, it is a brush up version of previous models and it is created with some collaborated ideas from its antecedent models. While creating the VGG19 architecture the size was kept fixed and it was (224*224). In that architecture a single initialization held and that was from every single picture element a value was deducted and that was typical RGB value. In VGG19, number of convolutions are sixteen and with that there are also three completely interconnected layers.
One of the important elements of convolution is a little kernel and the measurement of that kernel is (3*3) along with a single pixel. Max pooling layers are a key component of VGG19 and they are five in numbers and here the size of kernel is (2*2). Furthermore, L 2 regularization is employed by a component to correct heavy weights. For illustrating a connection within input and output three completely interconnected layers play a vital function. Moreover, it gives a benefit of maximizing early accomplished systems.
There are several approaches of VGG19. VGG19 is very much essential for carrying out particular duties. In addition, pretrained networks are particularly effective in organizing vast stuffs. In many cases VGG19 is used for different purposes as adap-

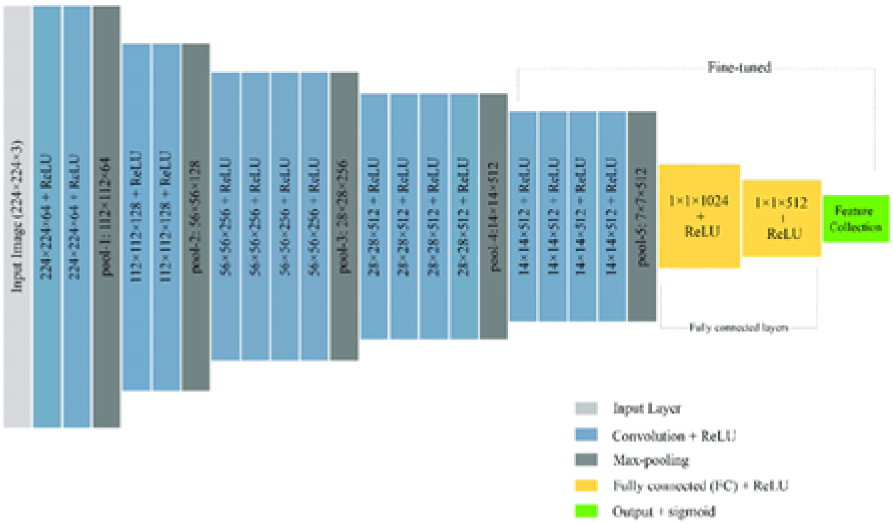


Figure 3.7: VGG19 Model Architecture[39]

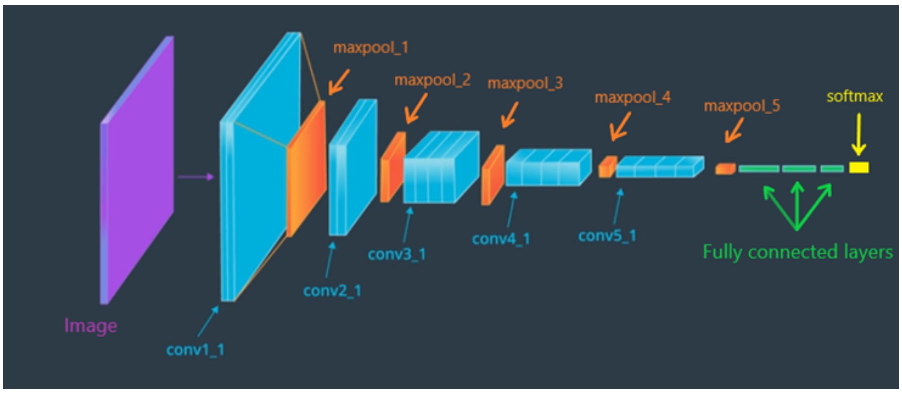


Figure 3.8: VGG19 Architecture [39]

tive learning. The significance of VGG19 in getting better result is notable.

Specific attributes of the code: Extra convolutional layers added to VGG-16 model. A dense layer of weight 100, LeakyRelu as activation function. It is followed by a Dense layer of 50, LeakyRelu activation then a desnse layer with the number of classes and activation function softmax. We try to train for 50 epochs with an early stopping function of patience 20.Optimizer used is RmsProp with a learning rate 0.0001.

3.2.4 Inception v3 [40]

Inception network was once thought to be the most advanced deep learning architecture(or model) for correcting image detection and recognition problems.It has achieved a turning point in CNN classifiers whereas the former models were getting into the detailed parts in order to bring improvements on their performances.It emphasizes on the speed and how accurate the performances are.When compared to VGGNet,the rate of error was lower.Inception network uses 1x1 convolution which is used for the reduction of computation.Without the use of 1x1 convolution,5x5 convolution is used below:

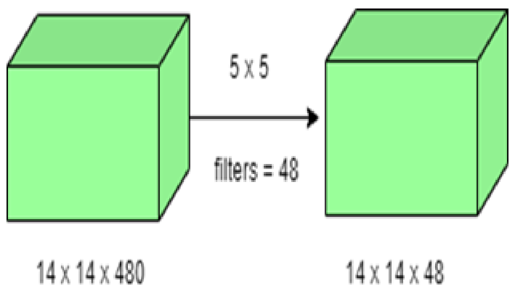


Figure 3.9: Inception v3 Model Architecture [40]

Number of operations involved here is $(14{\times}14{\times}48) \times (5{\times}5{\times}480) = 112.9$M Using $1{\times}1$ convolution:

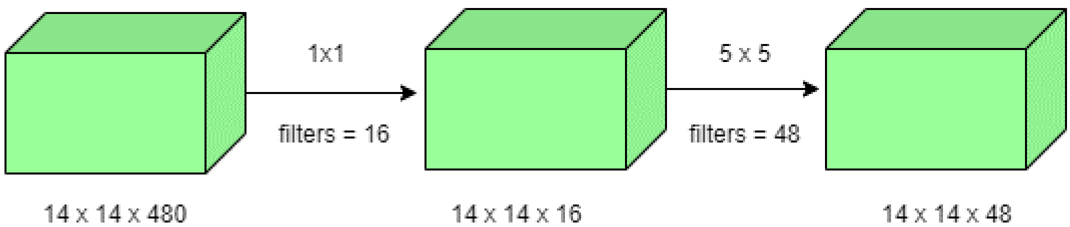


Figure 3.10: Inception v3 Model Architecture [40]

Number of operations for $1{\times}1$ convolution = $(14{\times}14{\times}16) \times (1{\times}1{\times}480) = 1.5$M Number of operations for $5{\times}5$ convolution = $(14{\times}14{\times}48) \times (5{\times}5{\times}16) = 3.8$M After addition we get, $1.5\text{M} + 3.8\text{M} = 5.3\text{M}$
Inception model with dimension reductions:
Deep convolutional networks are not cheap but with the introduction of 1x1 convolution it could be made cheaper.Before adding 3x3 and 5x5 convolutions,the number

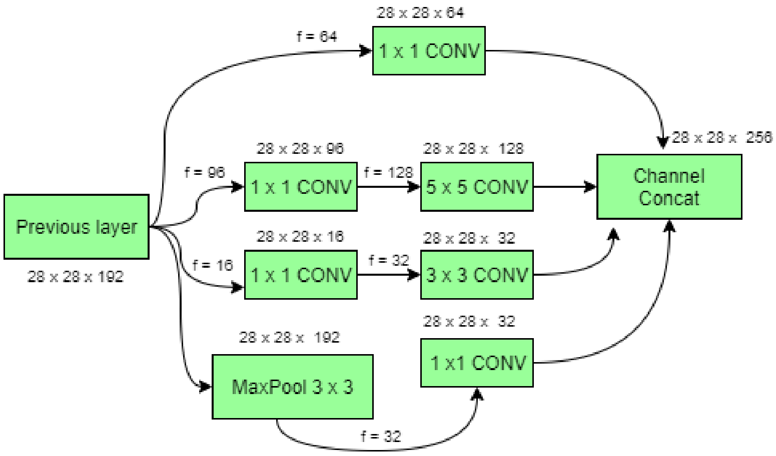


Figure 3.11: Inception model with dimension reductions[40]

of input channels are made limited and 1x1 convolution is introduced after the max-pooling layer.

GoogLeNet Architecture of Inception Network: The summation of all the layers in this architecture adds up to 22.A neural network architecture is built with the help of dimension reduced inception module which is known as GoogLeNet (Inception v1).9 modules are adjusted uniformly.Due to the introduction of global average pooling system,it calculates the mean of every feature map which decreases the number of parameters used.Eventually,Inception network has become a priority compared to the former different types of models used in CNN.Without changing the speed and accuracy,the computational expense has become cheaper.

Architectural Changes in Inception V2: In this architecture,two 3x3 convolutions take the place of a single 5x5 convolution.It works at a higher speed and takes less time which is an advantage and this takes place because the cost of 5x5 convolution is more than 3x3 convolution.Hence the effect of this architecture is higher as two 3x3 convolution is being used instead of a single 5x5 convolution.The diagram below shows an example:

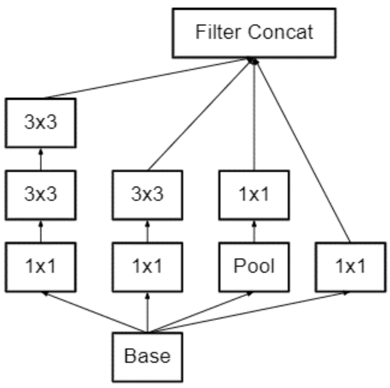


Figure 3.12: Architectural Changes in Inception V2[40]

Architectural Changes in Inception V3: This contains all the structures of Inception V2 with some additions and alterations.7x7 factorized convolution and RMSprop optimizer are being used.Auxiliary layer having complete connection of layers consists of batch normalization.Label Smoothing Regularization is a process through which the result of label-dropout is approximated at a regular basis while the training takes place. Thus disabling the classifier to predict a class and the improvement rate equals to 0.2

Specific attributes of the code: Version 3 of the separable convolutional layer model Inception. The last output after convolution filter application is flattened and a Dense layer with weight 1024 applied with ReLu activation followed by sigmoid activation on the 4 different classes. We use SGD optimizer with learning rate of 0.0001. Model is fitted for 50 epochs with early stopping function with patience 20.

3.2.5 Xception[41]

This model was proposed by Franchois Chollet.The Inception architecture has been extended to form Xception model which takes the place of standard inception modules using Separable Convolutions deeply.Xception model reverses the steps that are being used in Inception model.It uses the filters on every depth map and eventually decreases the space in the input layer with the help of 1x1 convolution which is applied surrounding the depth.

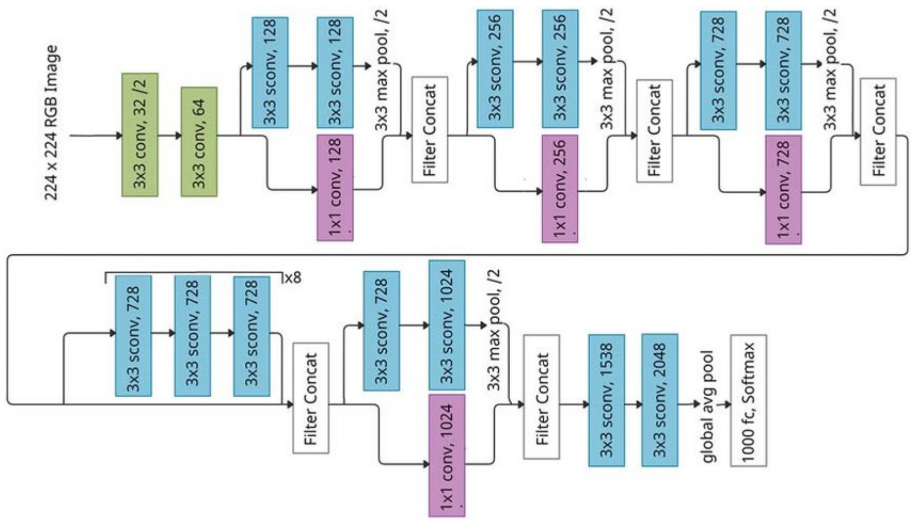


Figure 3.13: Xception Model Architecture [42]

This is how an Xception model looks like.The data enters the entry flow at the very beginning and after it goes to the middle flow,it repeats for eight times and eventually leaves through the exit flow.
In terms of computation time,classical convolution has become more effective.However,classical convolution has been replaced by Depthwise Separable Convolutions.

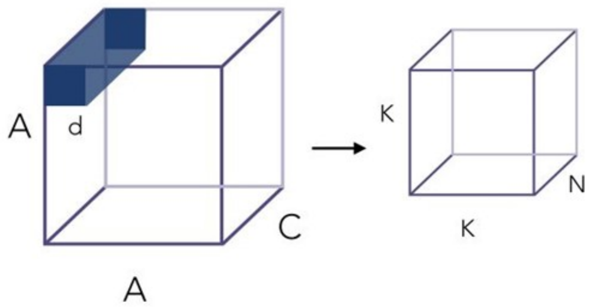


Figure 3.14: Depthwise Separable Convolutions [41]

The target for the introduction of Depth Separation Convolution was to reduce the cost and for this to be done,there are a couple of steps that should be taken into consideration, one is Depthwise Convolution another one is Pointwise Convolution The depthwise Separable Convolution blocks adds up with Maxpooling and connects with shortcuts similar to ResNet implementations.Although Depthwise convolution does not act in accordance with Pointwise convolution.However,the order has been turned around in the opposite direction which has been shown with the help of a figure below:

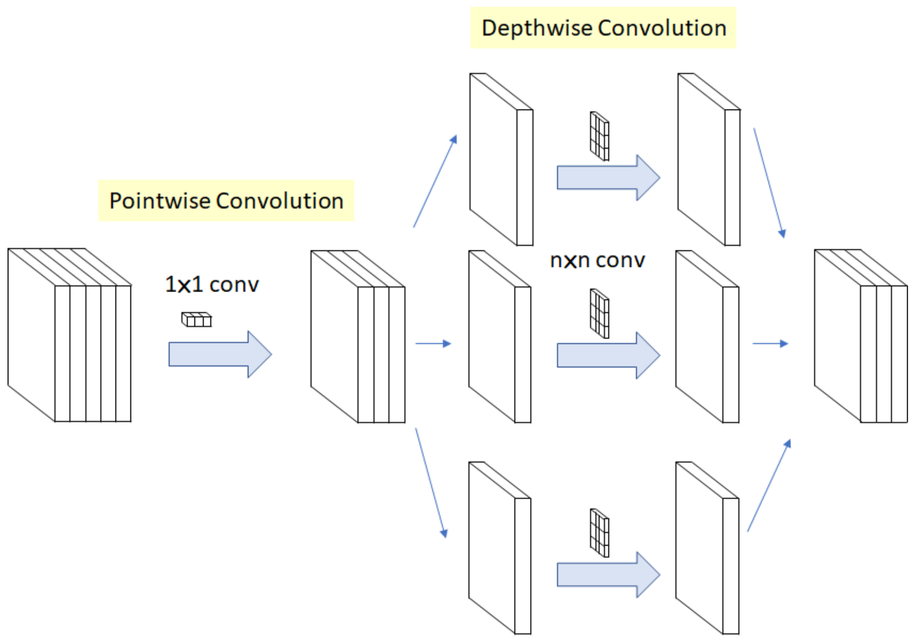


Figure 3.15: Separable Convolution [41]

Specific attributes of the code: Reduce On Plateau callback used with minimum learning rate 0.00001 and Optimizer used is RMSProp with learning rate 0.001. After the 3 separate flows, the model is compiled with adam optimizers. We run it for 50 epochs with an earlystopping function with patience 20.

Chapter 4

Data Augmentation

4.1 Data Set

Our random data set is divided into Clay Soil ,Laterite Soil, Yellow Soil and Black Soil. It provided up to 90% accuracy in our classifier models indicating legitimacy and accuracy. On this data set we performed Data Augmentation as soil is difficult to distinguish in color and texture where a large amount of data is required to yield confident results of prediction.

We also collected data from different places of Bangladesh. We named that the data set as BD data set. Our BD data set divided into 4 classes. Clay Soil, Laterite Soil, Loam Soil and Sandy Soil. It also provided us to up to 95% accuracy in our classifier models indicating authenticity and accuracy.

4.1.1 Random Soil Samples Data Set

There are 4 classes for Random soil data set . 4 classes divided into different portion. We put 2264 random soil images on train folder and 350 random soil images on test folder.

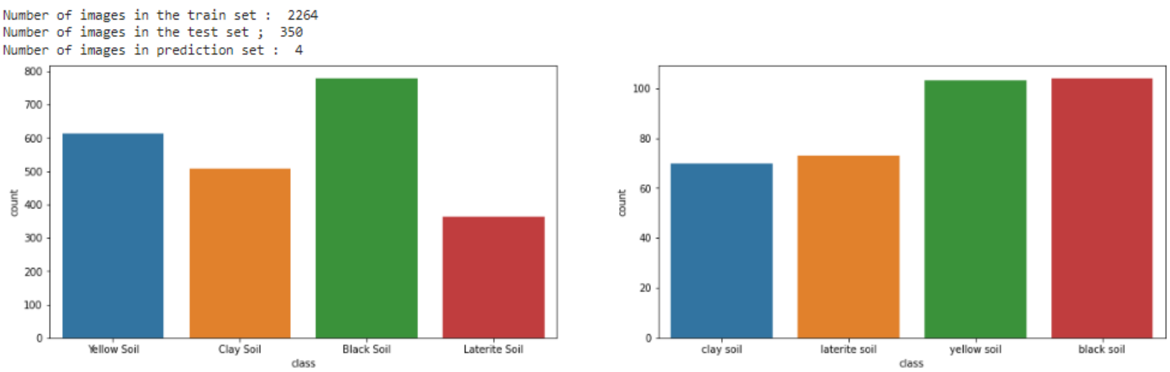


Figure 4.1: Random Soil Samples graph

Here are some raw soil samples pictures of Random soil data set:

Figure 4.2: Clay Soil

Figure 4.3: Black Soil

Figure 4.4: Laterite Soil

Figure 4.5: Yellow Soil

4.1.2 BD Soil Samples Data Set

We have also collected the Bangladeshi Soil Samples from different places of our country. It has been also divided into 4 classes. We have put 4096 images of Bangladeshi soil into to the train folder and 790 images in test folder.

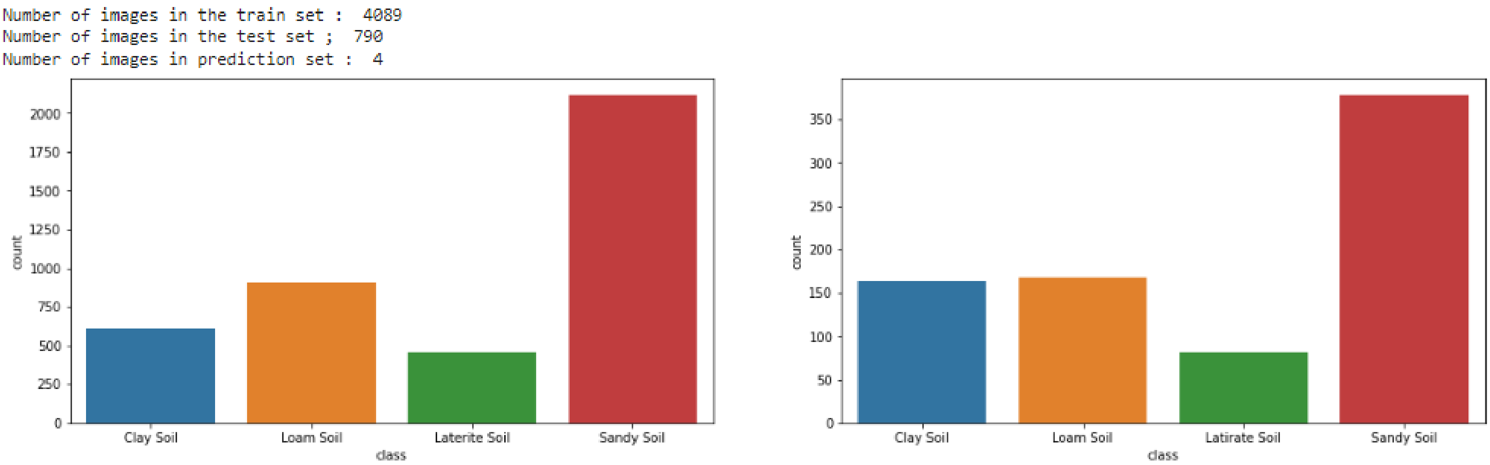


Figure 4.6: BD Soil Samples graph

Here are some raw samples of BD soil:

Figure 4.7: Clay Soil (BD)

Figure 4.8: Laterite Soil (BD)

Figure 4.9: Loam Soil (BD)

Figure 4.10: Sandy Soil (BD)

4.2 Image Augmentation

CNN Models required large amount of data set to get a better accuracy rate. But firstly the data set was so small that is why we have applied image augmentation to enlarge the date set quantity. So the data sets increased by changing the vector size of the image. We are successful by using this stragies. Our augmentations were performed using the parameters specified in the following table:

Data Augmentation	
Type of Augmentation	**Range of Values**
Degree of Rotation	-40 - 40
Shifting towards width (In fraction)	-0.2 - 0.2
Shifting towards height (In fraction)	-0.2 - 0.2
X axis zoom (In percentage)	0 - 20
Y axis zoom (In percentage)	0 - 20

Table 4.1: Data Augmentation Parameters

We then performed calculations using Keras API in python and pretrained models from said API. After doing the augmentation, some samples of the Data set:

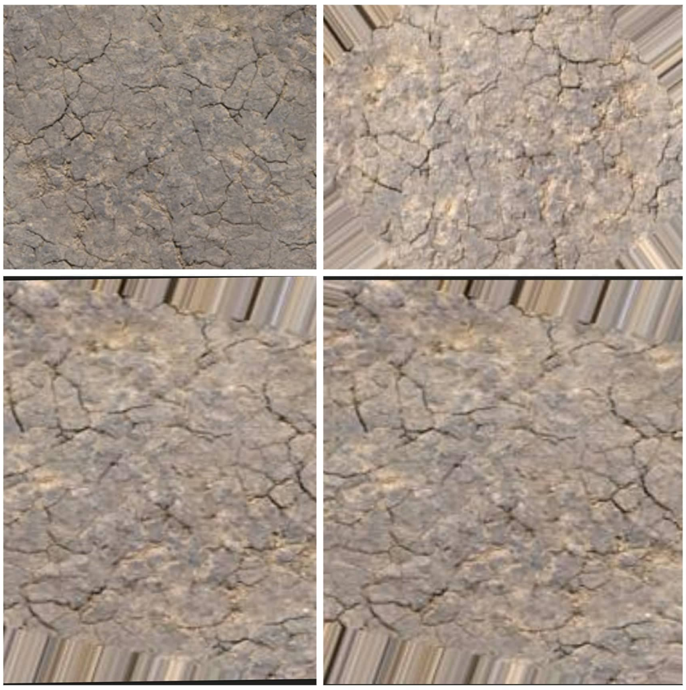


Figure 4.11: Augmented Images of Clay soil

This is how the data appears after the image augmentation. At the end of each session, the model was evaluated and its parameters were modified as needed using a tiny sample of the validation data set. However, as the validation set was the primary focus of parameter optimization,
The model could prefer the validation set. Consequently, we continued
the particular test set for which the model was never given access during training. Only after the entire training process had been completed was the model evaluated on the test set completed. The training data was then improved using the supplied

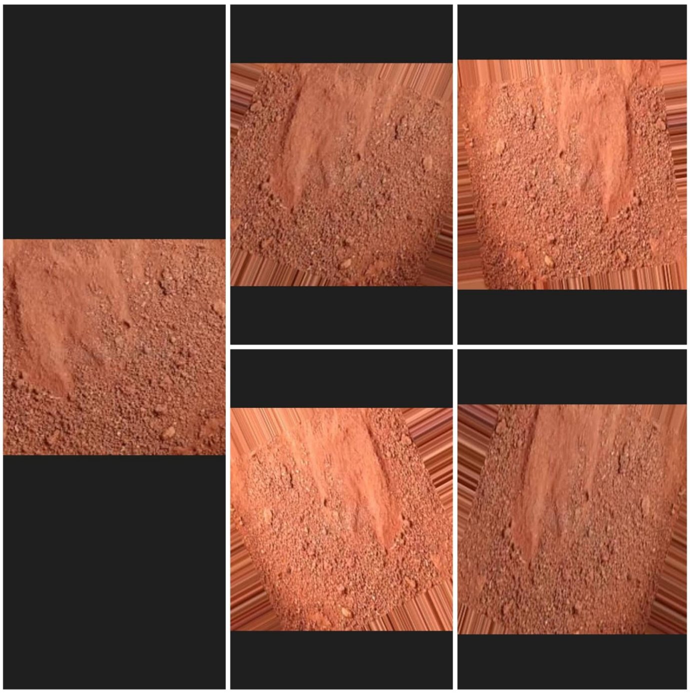


Figure 4.12: Augmented Images of Clay soil Laterite

settings to stop table 4.1 from prematurely becoming over-fitted. Each of the three image phases also has its called pixel values.

Chapter 5

Implementation and Result Analysis

The implementation of the proposed model for soil texture prediction is described in this chapter. We have applied many epochs in the training and validation data sets of calculate accuracy an loss. During performing training on the entire data set , prior to training, each image was reduced in size to 224*224 pixels. And our specification of device where the calculation was performed is Intel(R) Core(TM) i5-8300H CPU @ 2.30GHz, 8 gigabyte RAM, GTX 1050ti GPU. Validation accuracy varied slightly, despite training accuracy continuing to get better. Validation accuracy varied little, despite training accuracy continuing to become better. Now, we are going to describe the results after implementing different models on two different data sets.

5.1 Results of Different Models Using Random Data set of Soil Textures

We have taken the sample of 2500 images and split into a 80:20 ratio and implemented the following image classification Neural Network algorithms using them: VGG16, ResNet50, VGG19, Inception v3, Xception and Perceptron. 80% of our dataset was used to train the models and 20% to test its prediction capabilities. The dataset used was a random batch of soil divided into 4 classes by soil types.

Model Name	Trainable Parameters	Training Accuracy	Test Accuracy
VGG16	6,456,196	82.88%	91.43%
ResNet50	31,956,868	95.43%	96.86%
VGG-19	20,024,384	89.42%	91.42%
Inception v3	8,613,060	88.29%	90.86%
Xception	20,806,952	83%	85%

Table 5.1: Accuracy of the implemented models (Random Data Set)

Table 5.1, it is evident that in every case test accuracy is more than (90%) execpt Xception which is (85%) . Out of these models, test accuracy of ResNet50 is highest (96.86%). Similarly, in case of training accuracy the accuracy is almost same for ResNet50 (95.43%) is the highest. On the other hand, the lowest accuracy we get from Xception. In VGG16, VGG19 and Inception v3 we get a decent percentage of test accuracy and training accuracy.

5.1.1 Test Accuracy and loss Curve of All Models (Random Data Set)

We also get test accuracy curve and loss curve of these models. Here we are going to describe about it.
VGG16 : VGG16 shows a declining loss curve though the gradient is low due to relearning data repeatedly in all layers. But it has a better learning rate and a loss curve that relates more to the pattern oof the training loss curve.

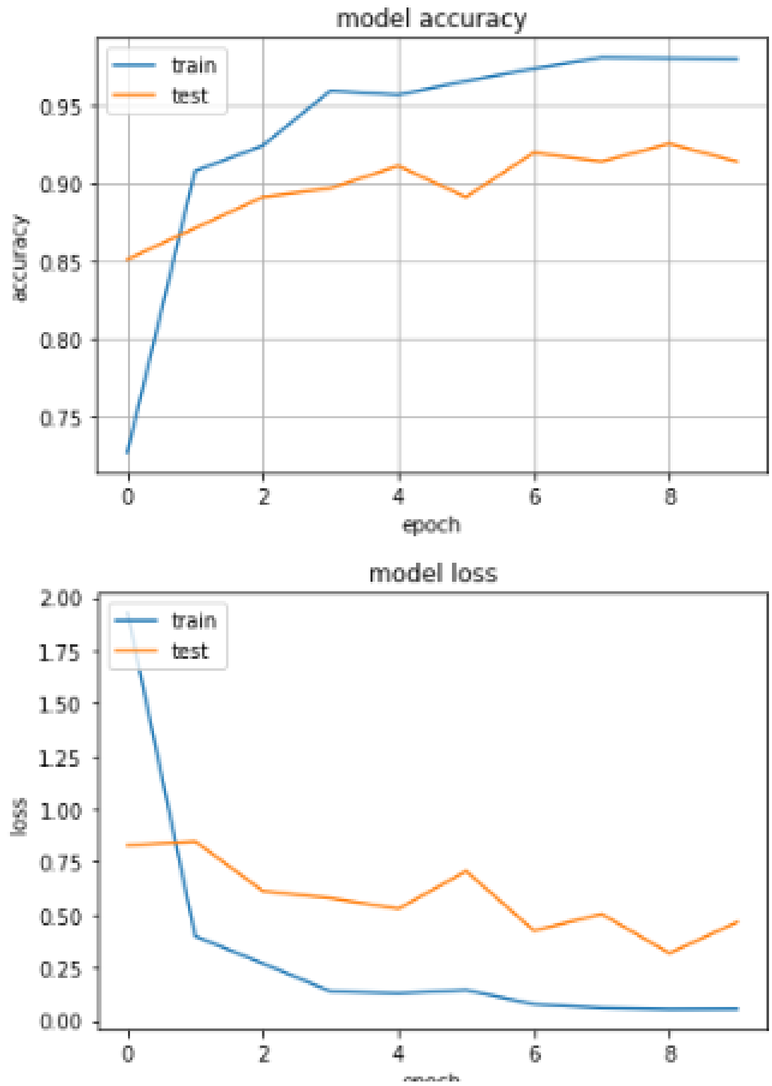


Figure 5.1: VGG16 test accuracy and loss curve(Random Data Set)

ResNet50: According to the table 5.1 gives a high accuracy of 96.86% due to the use of residual networks that do not require constant relearning of the images. The loss cure shows a steady decline apart from few anomalies the data set is trained well and fluctuations are limited.

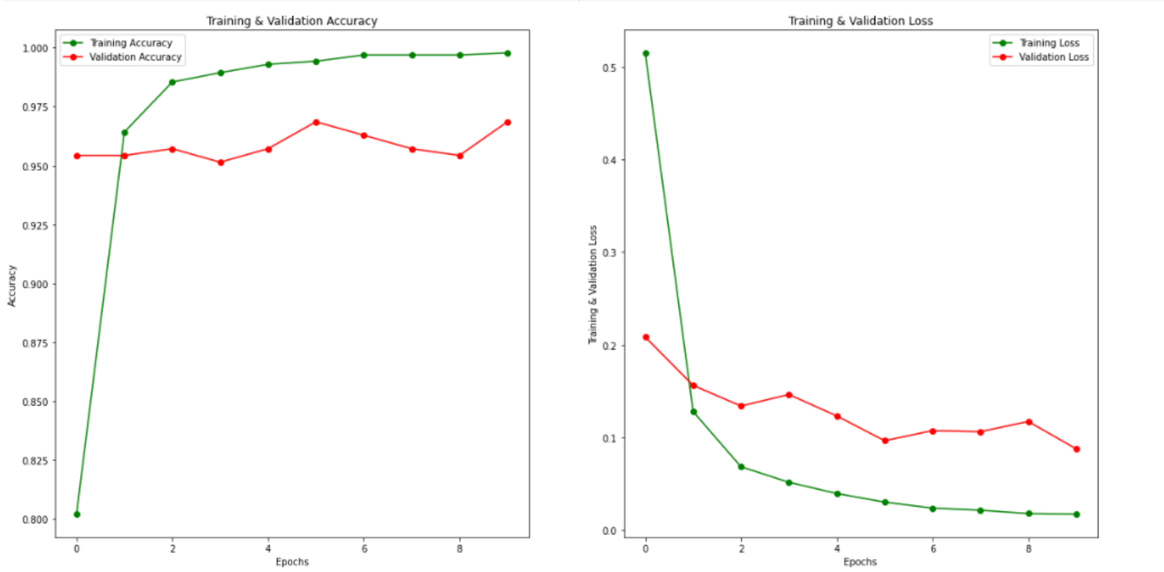


Figure 5.2: ResNet50 test accuracy and loss curve (Random Soil Data Set)

VGG19: VGG19 shows a lower accuracy than ResNet due to added layers and due to constant relearning and accessing neurons each time the loss curve shows unsteadiness. It has struggled a bit due to underrepresented data though the accuracy of prediction is 91.42%.

Figure 5.3: VGG19 test accuracy and loss curve (Random Soil Data Set)

Inception v3: It shows a perfect learning curve and compared to training loss curve the validation loss curve shows relative and steady decline due to mainly its auxiliary classifiers which reduce errors. It is also faster due it's factorized convolutions.

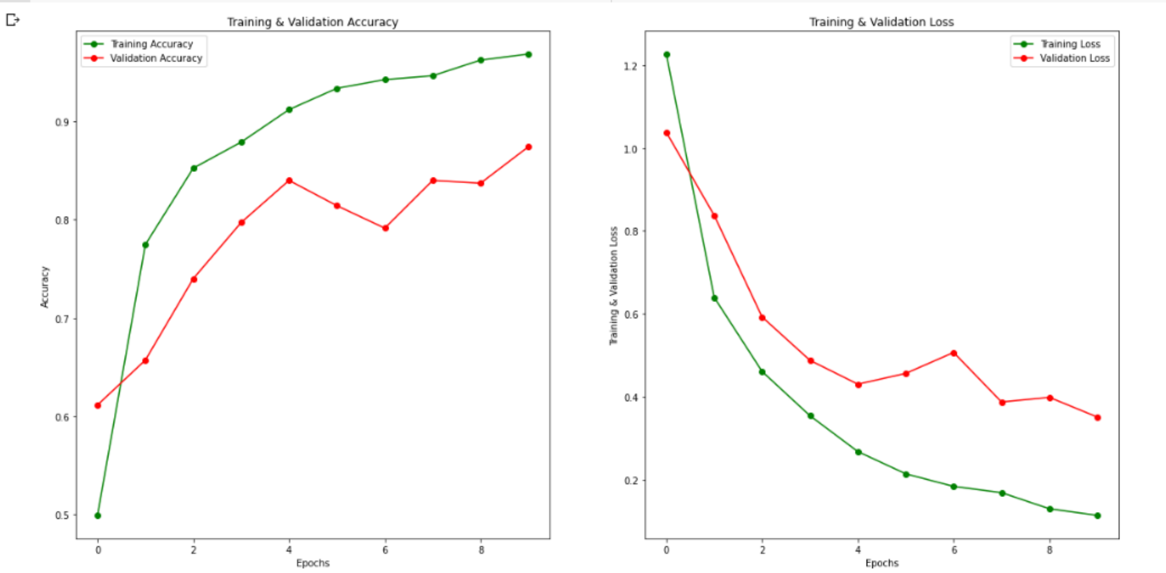


Figure 5.4: Inception v3 test accuracy and loss curve (Random Soil Data Set)

Xception: Xception shows a declining loss curve over 10 epochs. It is a slow process bound to give better results when spread over 200 epochs.

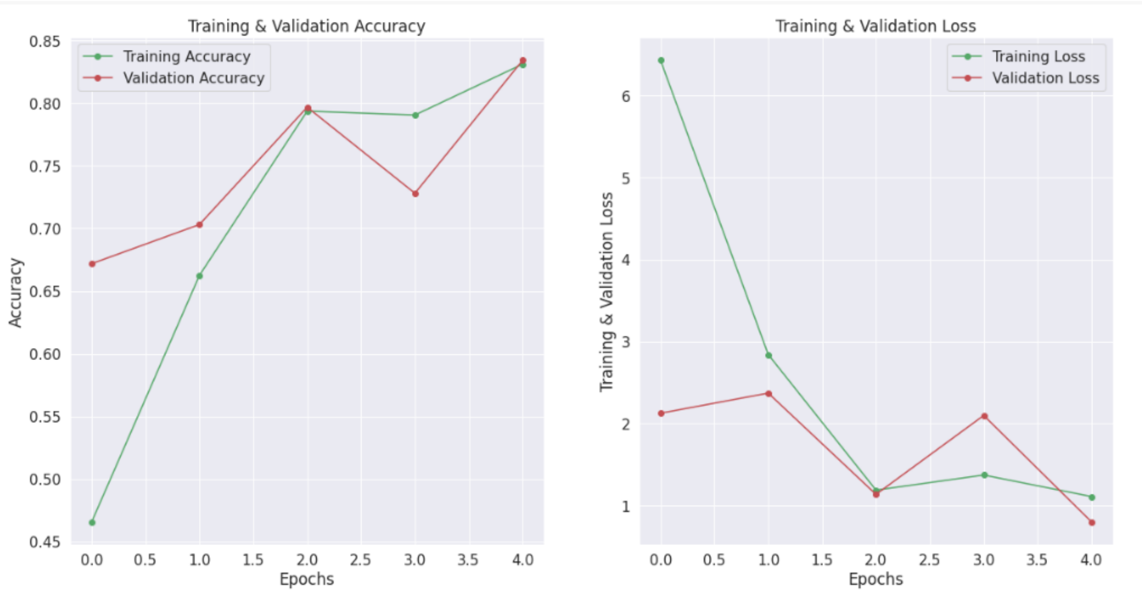


Figure 5.5: Xception test accuracy and loss curve (Random Soil Data Set)

5.1.2 Confusion Matrix and Classification Report of Implemented Models (Random Soil Data Set)

The table 5.2 shows the proportion to which the prediction is accurate relative to training data. On average best performance is given by InceptionV3 and VGG19.

Model	Clay Soil	Laterite Soil	Yellow Soil	Black Soil
VGG19	42	70	1e+02	1e+02
VGG16	45	70	24	Le+02
Inception v3	50	41	90	103
Xception	1e+02	41	44	1e+02
ResNet50	26	17	43	59

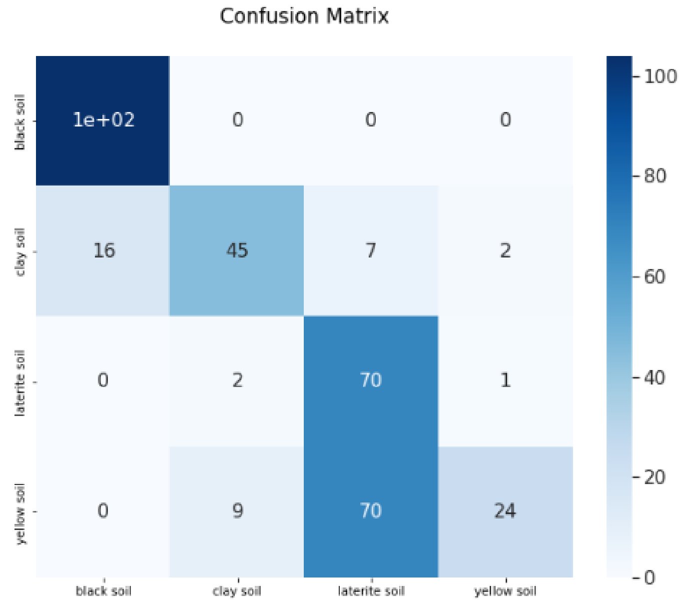
Table 5.2: Proportion of Accuracy Between Train and Test (Random Soil Data Set)

The equation for the classification from confusion matrix :

$$\text{Recall} = \text{TruePositives} \ / \ (\text{TruePositives} + \text{FalseNegatives}\ ) \tag{5.1}$$

$$F_1 = \left(\frac{2}{\textbf{recall}^{\ -1} + \ \textbf{precision}^{\ -1}} \right) = 2 \cdot \frac{\textbf{precision} \ \cdot \ \textbf{recall}}{\textbf{precision} \ + \ \textbf{recall}} \tag{5.2}$$

VGG16: The classifiers completeness and precision are shown in the classification report of Random soil dataset. As seen on the matrix, the proportionality of train to test data as it comes to prediction success of the test dataset is 24, 70,45,102 for yellow, laterite ,clay and black respectively. The classifiers completeness and precision acts as an evident in the classification report of Random soil dataset. The f1-score is 37,64,71 and 93 with yellow soil showing least strength. The data set for random has its cracks.

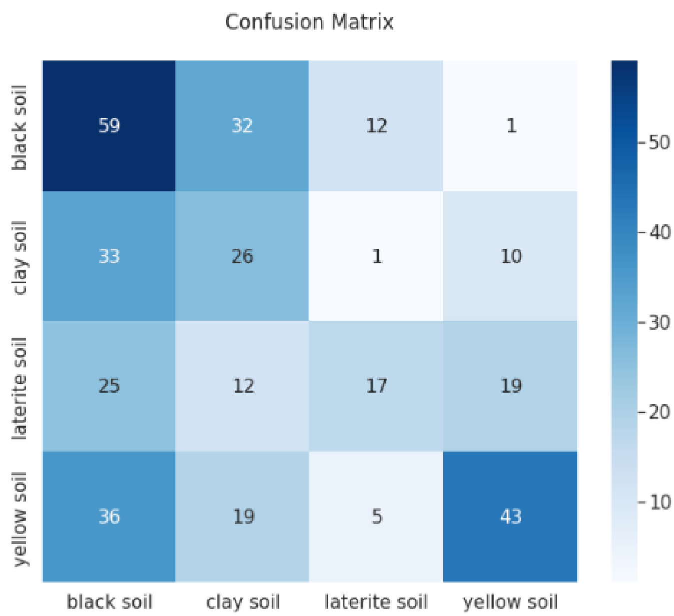


Classification Report

	precision	recall	f1-score	support
black soil	0.87	1.00	0.93	104
clay soil	0.80	0.64	0.71	70
laterite soil	0.48	0.96	0.64	73
yellow soil	0.89	0.23	0.37	103
accuracy			0.69	350
macro avg	0.76	0.71	0.66	350
weighted avg	0.78	0.69	0.66	350

Figure 5.6: VGG16 Confusion matrix and classification report (Random Soil Data Set)

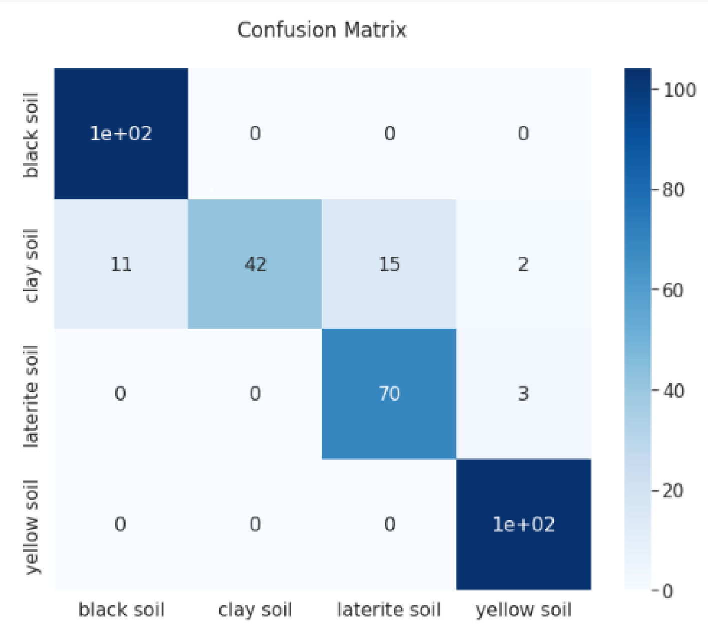
ResNet50: As seen on the matrix, the proportionality of train to test data as it comes to prediction success of the test dataset is 43,17,26,89 for yellow, laterite ,clay and black respectively.Random soil dataset. The f1-score is 49,31,33,46. This classification has lower completeness and precision.




```
Classification Report

               precision    recall  f1-score   support

   black soil       0.39      0.57      0.46       104
    clay soil       0.29      0.37      0.33        70
laterite soil       0.49      0.23      0.31        73
  yellow soil       0.59      0.42      0.49       103

     accuracy                           0.41       350
    macro avg       0.44      0.40      0.40       350
 weighted avg       0.45      0.41      0.41       350
```

Figure 5.7: ResNet50 Confusion matrix and classification report (Random Soil Data Set)

VGG19: As seen on the matrix, the proportionality of train to test data as it comes to prediction success of the test dataset is 102,70,42,102 for yellow, laterite ,clay and black respectively. The classifiers completeness and precision are evident in the classification report of Random soil dataset. The f1-score is 98,89,75,95. This model performs better than vgg-16 due to the added layers and as f1 score proves, more precision.



Classification Report

	precision	recall	f1-score	support
black soil	0.90	1.00	0.95	104
clay soil	1.00	0.60	0.75	70
laterite soil	0.82	0.96	0.89	73
yellow soil	0.95	1.00	0.98	103
accuracy			0.91	350
macro avg	0.92	0.89	0.89	350
weighted avg	0.92	0.91	0.90	350

Figure 5.8: VGG19 Confusion matrix and classification report (Random Soil Data Set)

Inception v3: 90,41,50 and 103 are the train to test accuracy of yellow, laterite , clay and black soil. The f-1 scores are84,66,80,88%. The classification was done with high accuracy yet the dataset shows cracks especially for laterite soil.

Model Accuracy 0.7457142857142857

	precision	recall	f1-score	support
black soil	0.66	0.97	0.78	104
clay soil	1.00	0.61	0.76	70
laterite soil	0.81	0.30	0.44	73
yellow soil	0.75	0.92	0.83	103
accuracy			0.75	350
macro avg	0.81	0.70	0.70	350
weighted avg	0.79	0.75	0.72	350

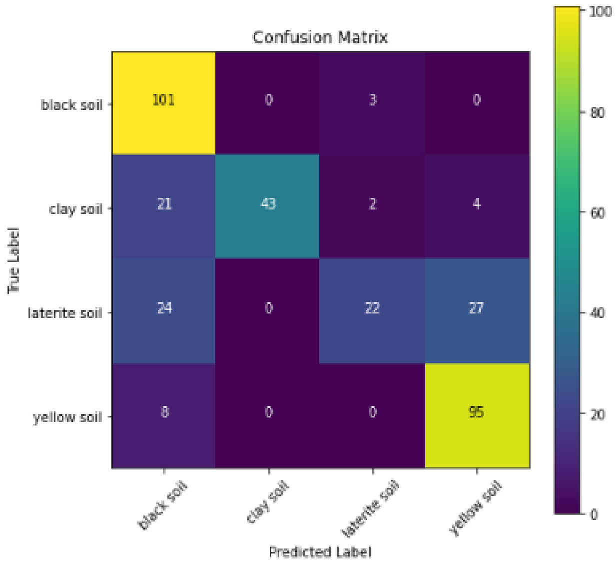
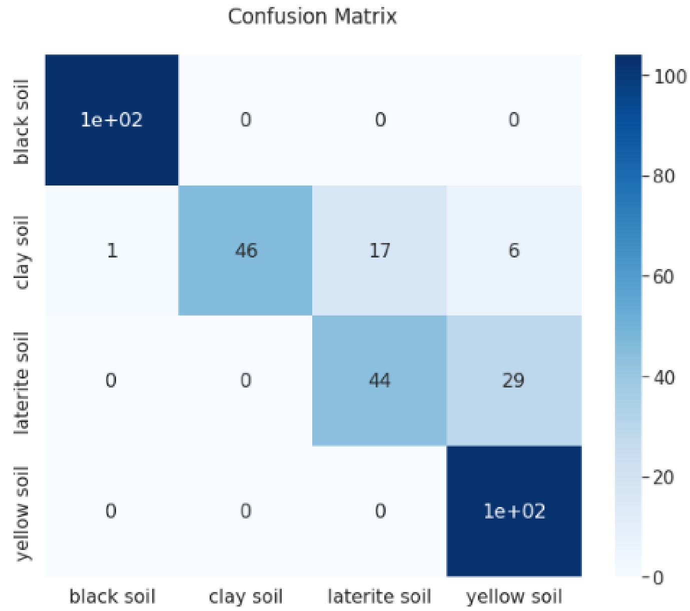


Figure 5.9: Inception v3 Confusion matrix and classification report (Random Soil Data Set)

Xception: 100,46,44,100 are the completeness and train to test success ratio for black,clay,laterite and yellow soil in order.The classification report gives and f1-score of 100,79,66,89 percent which is quite high for black soil yet lower for others.




```
Classification Report

               precision    recall  f1-score   support

   black soil       0.99      1.00      1.00       104
    clay soil       1.00      0.66      0.79        70
laterite soil       0.72      0.60      0.66        73
  yellow soil       0.75      1.00      0.85       103

     accuracy                           0.85       350
    macro avg       0.86      0.81      0.82       350
 weighted avg       0.86      0.85      0.84       350
```

Figure 5.10: Xception Confusion matrix and classifier report (Random Soil Data Set)

5.2 Results of Different Models Using BD Soil Texture Data set

We used same models for BD soil texture data set and got slightly different results from previous data set. Here we will discuss about results of it.

Name of the models	Parameters	Test Accuracy	Training Accuracy
VGG16	6,456,196	98.14%	97.59%
VGG19	31,956,868	96.97%	99.62%
ResNet50	21,170,884	98.55%	98.05%
Inception v3	8613060	97.43%	99.37%
Xception	20,806,952	79%	82%

Table 5.3: Accuracy of the implemented models (BD Soil Data Set)

From the above table, it is evident that in every case test accuracy is more than (90%) and same thing goes for training Accuracy too. Out of these models, test accuracy of ResNet50 is highest (98.55). Similarly, in case of training Accuracy the accuracy is almost same for VGG19 (99.62%) and Inception V3 (99.37%) which can be considered as highest. On the other hand, Xception got less accuracy than others.

5.2.1 Test Accuracy and Loss Curve of All Models (BD Soil Data Set)

VGG16: The graphs in Figure 5.6 show the accuracy history and loss history in between a range of 60 epochs of VGG16 architecture model. These figures are given as a percentage in accuracy and loss history. By increasing number of epochs, the accuracy gets higher due time and the loss, it has a smooth downward trajectory.

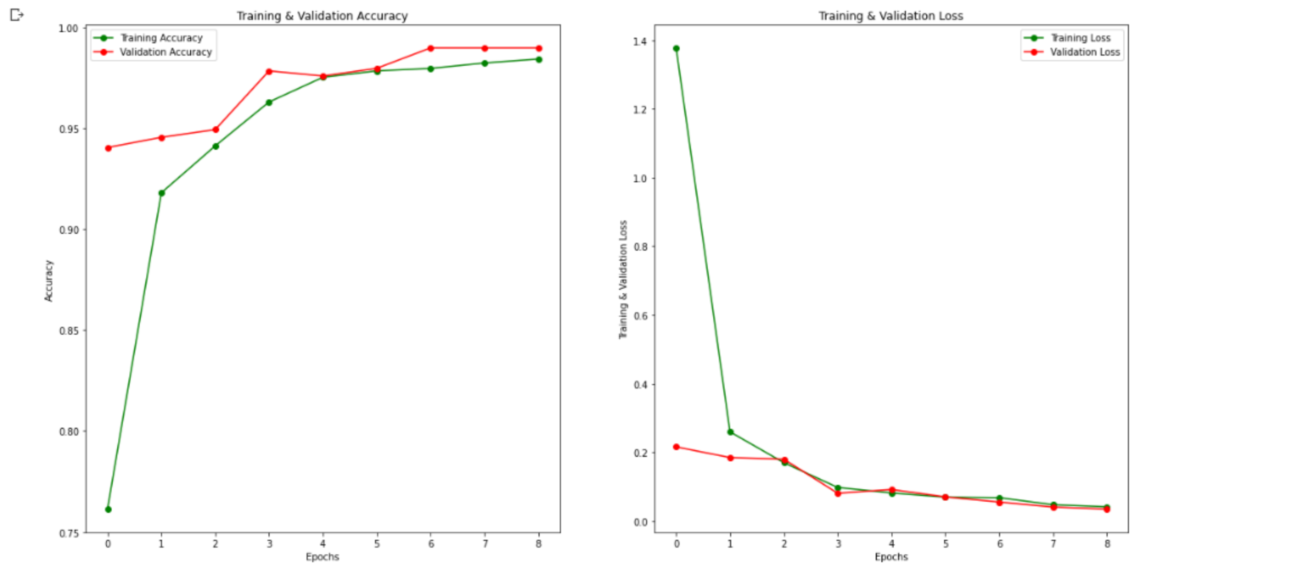


Figure 5.11: VGG16 test accuracy and loss curve(BD Soil Data Set)

ResNet50: Figure 5.7 gives the idea of the accuracy history and loss history in between a range of 20 epochs of ResNet50 architecture model. By the time and epoch increases, the accuracy goes upwards and the loss goes downwards.

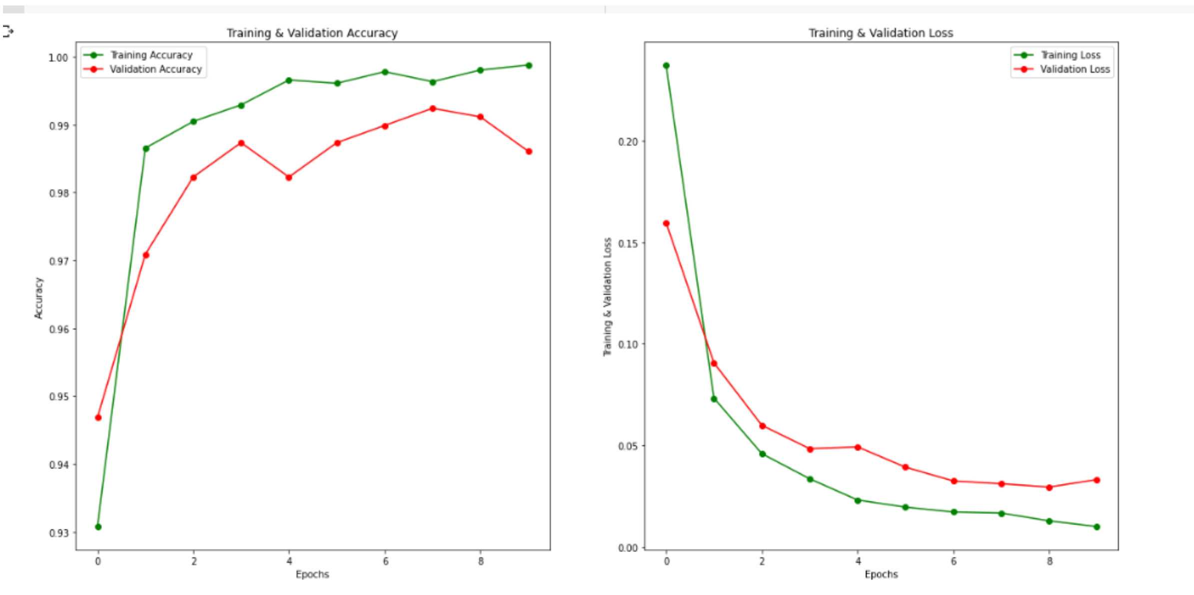


Figure 5.12: ResNet50 test accuracy and loss curve (BD Soil Data Set)

VGG19: The graphs in Figure 5.8 display the accuracy history and loss history for the VGG19 architecture model. When the epoch number increases the training and training Accuracy increases differently. And for the loss history, training loss decreases smoothly and validation loss remains between a range.

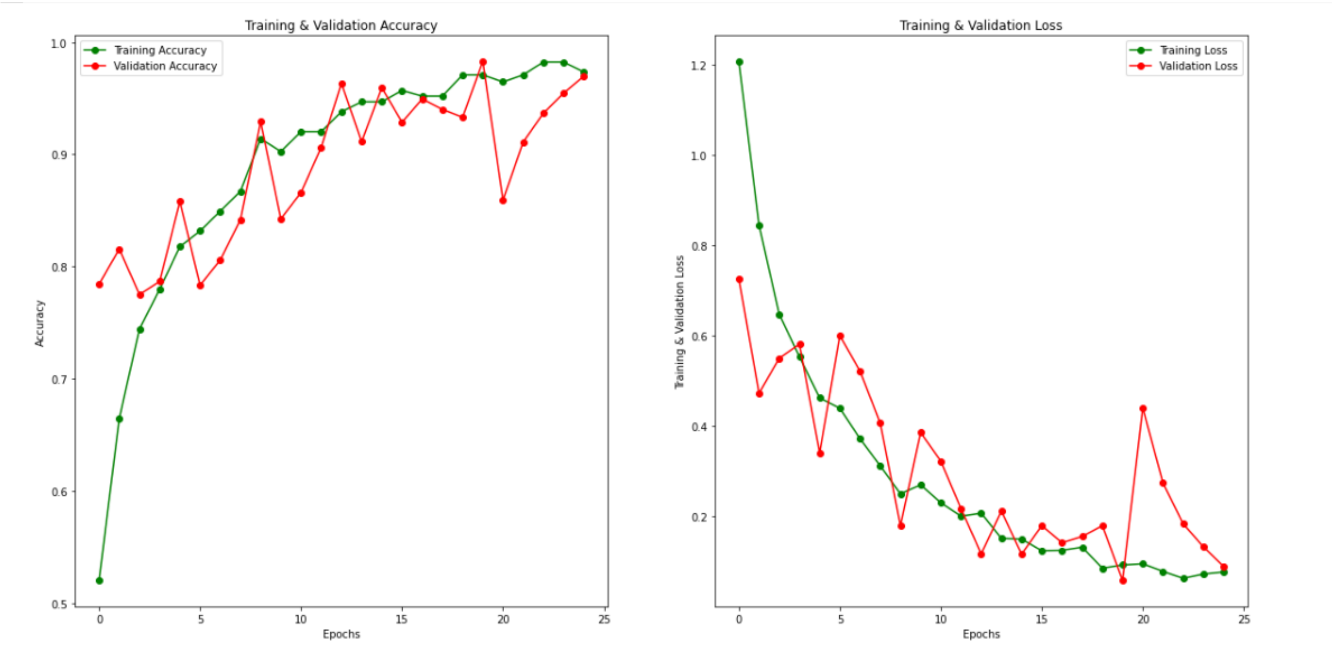


Figure 5.13: VGG19 test accuracy and loss curve (BD Soil Data Set)

Inception v3: Above the graph of figure 5.9 shows the training and test Accuracy history and the training and validation loss of the Inception v3 architectural model. Training and validation accuracy goes upwards due to the epoch number and training and validation loss goes downwards due to the increasing of epochs.

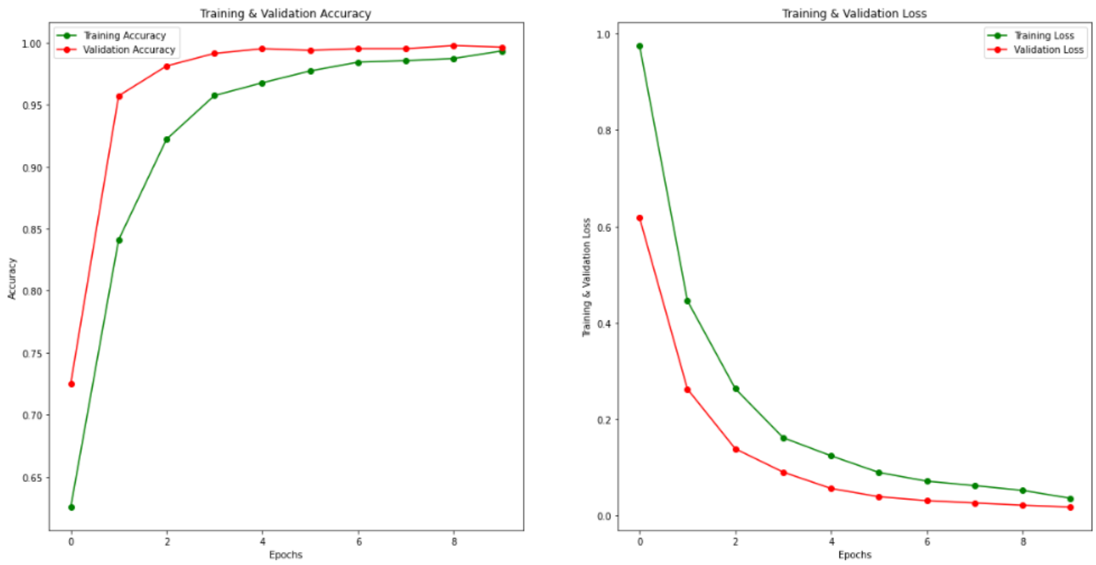


Figure 5.14: Inception v3 test accuracy and loss curve (BD Soil Data Set)

Xception: In this model we got lower accuracy and that is why it's loss curve different from others. In the figure 5.10 the difference between training accuracy and validation accuracy is much more than other models. Because of less epoch this model gives different result from others.

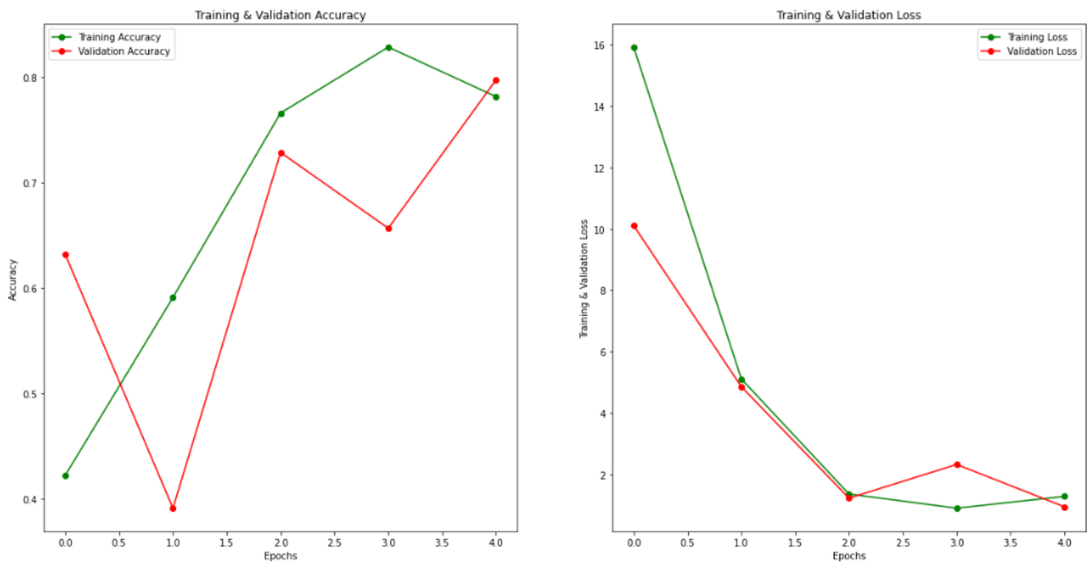


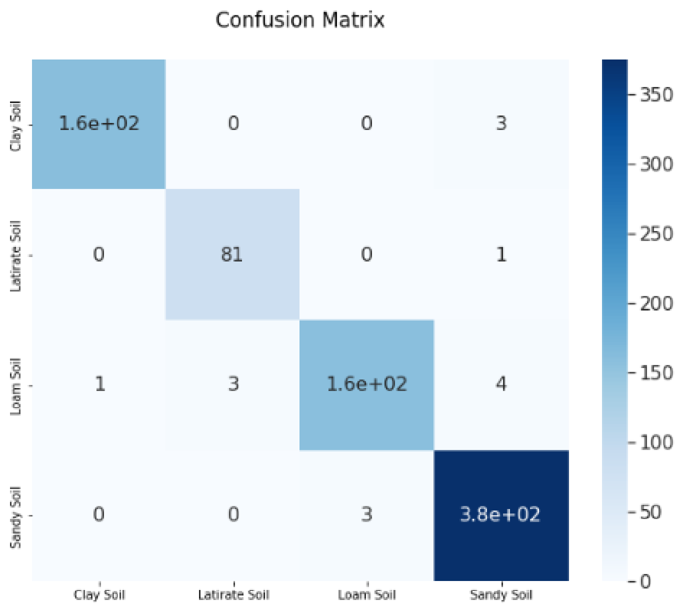
Figure 5.15: Xception test accuracy and loss curve (BD Soil Data Set)

5.2.2 Confusion Matrix and Classification Report of Implemented Models (BD Soil Data Set)

Model	Clay Soil	Laterite Soil	Loam Soil	Sandy Soil
VGG16	1.60e+02	81	1.60e+03	3.8e=02
VGG19	6.00E+02	4.20e+02	8.20e+02	2.00e+02
Inception v3	50	41	90	103
Xception	1.3e+02	53	1.3e+02	3.6e+02
ResNet50	1.60e+02	82	1.60e+02	3.80e+02

Table 5.4: Proportion of Accuracy Between Train and Test (BD Soil Data Set)

Random soil data gives poorer performance due which is not seen in Bangladesh soil dataset. Given such constraints our models perform well as seen in the confusion matrix results generated. From table 5.4 we can see that ResNet50 and VGG16 give almost same performance and VGG19 gives the best performance so far.
VGG16: The classifiers completeness and precision are evident in the classification report of Bangladesh soil dataset. As seen on the matrix, the proportionality of train to test data as it comes to prediction success of the test dataset is high with 378,167,81,162 for sandy, loam, laterite and clay respectively. The classifiers completeness and precision are evident in the classification report of Random soil dataset. The f1-score is 99,97,98,99 showing a strong data set and successful and accurate classification.
ResNet50: 378,162,82,163 are the completeness and proportionality of train to test accuracy for sandy, loam, laterite and clay soil respectively where as the f1-score is 99,98,99 and 99%. These results show the classifier and data set to be successful and strong respectively

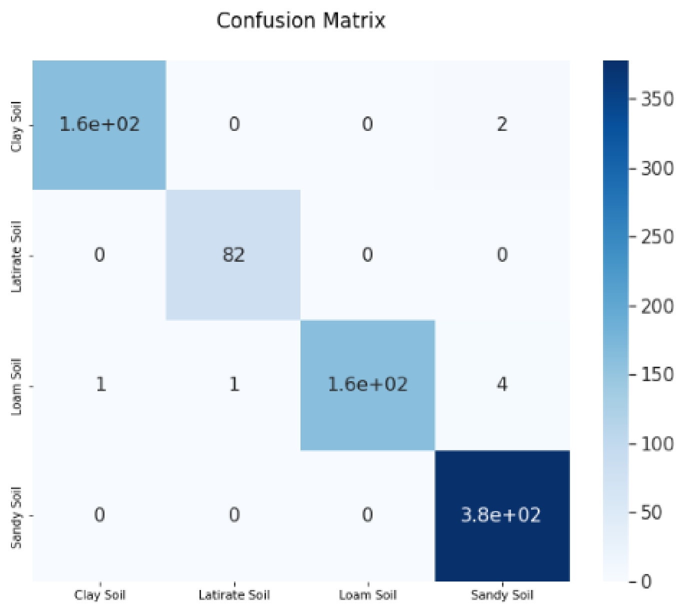


Classification Report

	precision	recall	f1-score	support
Clay Soil	0.99	0.98	0.99	163
Latirate Soil	0.96	0.99	0.98	82
Loam Soil	0.98	0.95	0.97	167
Sandy Soil	0.98	0.99	0.99	378
accuracy			0.98	790
macro avg	0.98	0.98	0.98	790
weighted avg	0.98	0.98	0.98	790

Figure 5.16: VGG16 Confusion matrix and classification report (Bd Soil Data Set)

VGG19: The classifiers completeness and precision are evident in the classification report of Bangladesh soil dataset. As seen on the matrix, the proportionality of train to test data as it comes to prediction success of the test dataset is extremely high with 2118,908,453,610 for sandy, loam, laterite and clay respectively. The classifiers completeness and precision are evident in the classification report . The f1-score is 98,94,96,98 showing a strong data set and successful and accurate classification.

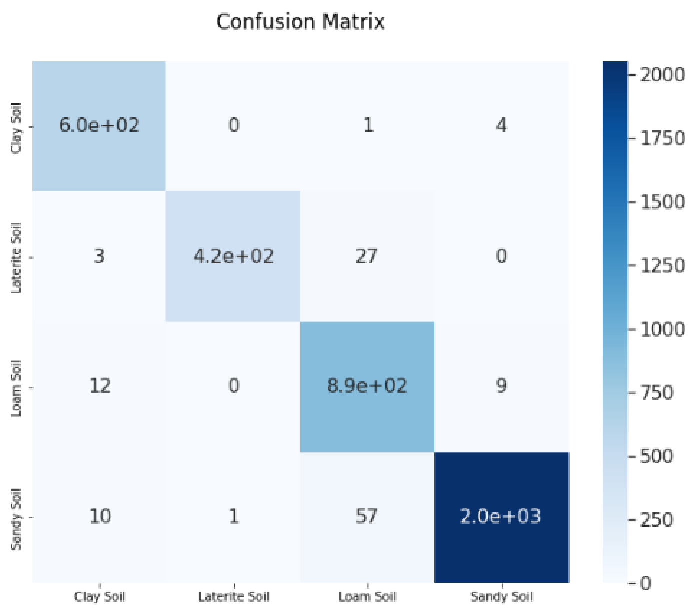


Classification Report

	precision	recall	f1-score	support
Clay Soil	0.99	0.99	0.99	163
Latirate Soil	0.99	1.00	0.99	82
Loam Soil	1.00	0.96	0.98	167
Sandy Soil	0.98	1.00	0.99	378
accuracy			0.99	790
macro avg	0.99	0.99	0.99	790
weighted avg	0.99	0.99	0.99	790

Figure 5.17: Resnet50 Confusion matrix and classification report (Bd Soil Data Set)

Inception-V3: 374,135,78 and 162 are the completeness of sandy, loam, laterite and clay soil respectively given by the confusion matrix. The values are high showing high rate of accuracy between train and test result.



Classification Report

	precision	recall	f1-score	support
Clay Soil	0.96	0.99	0.98	610
Laterite Soil	1.00	0.93	0.96	453
Loam Soil	0.91	0.98	0.94	908
Sandy Soil	0.99	0.97	0.98	2118
accuracy			0.97	4089
macro avg	0.97	0.97	0.97	4089
weighted avg	0.97	0.97	0.97	4089

Figure 5.18: VGG19 Confusion matrix and classification report (Bd Soil Data Set)

Xception: The confusion matrix for this model gives 130,53,130,360 for clay, laterite, loam and sandy respectively.It indicates strong completeness and predict capability. The classification report gives a 88,70,78 and 92 percent in order as f1-score. These values show that the model has classified the soil types successfully and with high accuracy,

```
Model Accuracy 0.7371428571428571
              precision    recall  f1-score   support

  black soil       0.62      1.00      0.77       104
   clay soil       0.97      0.54      0.70        70
laterite soil      0.88      0.41      0.56        73
 yellow soil       0.78      0.83      0.81       103

    accuracy                           0.74       350
   macro avg       0.82      0.70      0.71       350
weighted avg       0.79      0.74      0.72       350
```

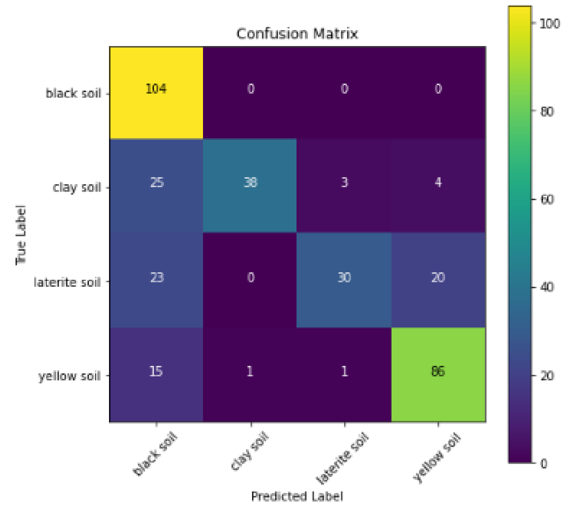


Figure 5.19: Inception v3 Confusion matrix and classification report (Bd Soil Data Set)

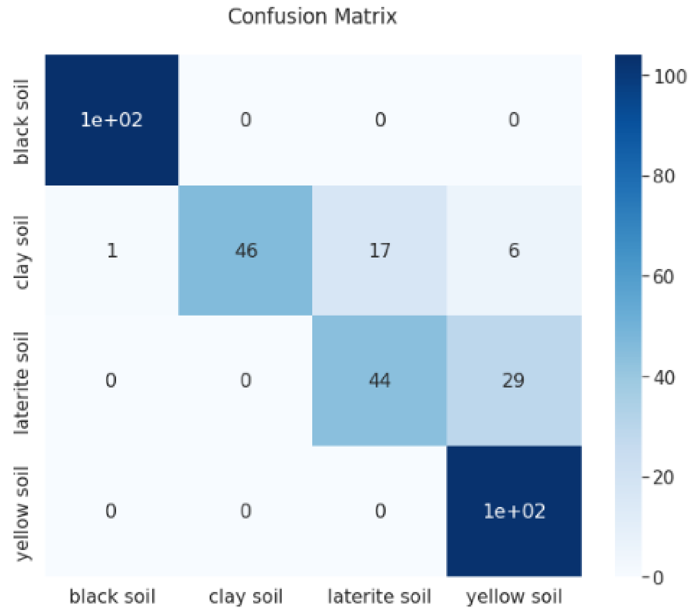
5.3 Test Accuracy Comparison Between Random Soil Samples Data set and BD Soil Samples Data set

We have applied 5 different models in both data set and we have got different test accuracy. In the given below table displays test accuracy of both data set for different particular models.

Name of the Models	Test Accuracy (Random Soil Data set)	Test Accuracy (BD Soil Data set)
VGG16	98.06%	98.14%
VGG19	91.42%	96.97%
ResNet50	96.86%	98.55%
Inception v3	90.86%	97.43%
Xception	85%	79%

Table 5.5: Test Accuracy Comparison

Firstly, after applying VGG16 in random soil samples data set, the test accuracy is (98.06%) and the test accuracy is almost same in case of BD soil samples data set (98.14). Here, we have got decent accuracy for both datasets. Secondly, we have got (91.42%) test accuracy after applying VGG19 in random soil samples data set and (96.97%) in BD soil samples data set. Particularly, in this section we have got better test accuracy for BD soil samples data set. Thirdly, in case of ResNet50 we have got



Classification Report

	precision	recall	f1-score	support
black soil	0.99	1.00	1.00	104
clay soil	1.00	0.66	0.79	70
laterite soil	0.72	0.60	0.66	73
yellow soil	0.75	1.00	0.85	103
accuracy			0.85	350
macro avg	0.86	0.81	0.82	350
weighted avg	0.86	0.85	0.84	350

Figure 5.20: Xception Confusion matrix and classifier report (BD Soil Data Set)

better test accuracy for random BD soil samples data set (98.55) but similarly the result is pretty good (96.86%) for random soil samples data set. Fourthly, the test accuracy is (90.86%) after applying Inception v3 to random soil samples data set and (97.43%) in case of BD soil samples data set. Here, we can say that, Inception v3 performed better for BD soil samples data set. On the other hand in case of Xception we got less than 90% of accuracy from the both data set. We get 85% test accuracy from random data set for BD soil samples it is 79%.

5.4 Comparison With Other Research Papers

We have studied several papers related to our research work aiming to have a decent knowledge and come out with some findings. To do our research, we have used two different types of datasets. First one is random soil samples data set and another one is soil samples from different areas of Bangladesh, which we named BD soil samples data set. In addition, comparing to other research papers we have used variety of data set. In paper [23], they have used four CNN models (VGG16, VGG19, ResNet50, InceptionV3) and they have got average test accuracy for VGG16 (91.55 %), (89.55%) for VGG19, (89.73 %) for ResNet50 and (90.87%) for Inception v3. We have also applied these models and we have got better test accuracy in VGG16, VGG19 and ResNet50 and in case of InceptionV3 the test accuracy is almost same (90.86%) for random soil samples data set but test accuracy (97.43%) is higher for

BD soil samples data set. In paper [25], they have used Inception v3 and they have got (98%) average test accuracy and, in our case, we have got (90.86%) for random soil samples data set and (97.43%) for BD soil samples data set. Moreover, for getting better accuracy and faster performance we have used ensemble method, which is basically a collaboration of three CNN models (VGG16, ResNet50, Inception v3). This is one the unique features of our research comparing to other research works.

Chapter 6

Conclusion and Future Work

To conclude, soil texture plays a very basic role in the agricultural arena and the development of crops highly dependent on soil texture quality. As a result, there is no alternative of having the best production without proper soil texture prediction. In addition, to minimize time and work pressure for cultivation soil texture prediction is a must. Different types of soil textures have been used for the purpose of research. Furthermore, a portable device is also suggested, which doesn't require any internet connection and it will be used for predicting the soil texture accurately on the basis of predefined dataset. Considering some factors, conventional neural networks are also a part of our research. A classic neural network ResNet50 is used for the betterment and efficient result for the purpose of our thesis.In addition, we have implemented another CNN architecture VGG16 which is regarded as an outstanding vision model architecture. Other models VGG19, Inception v3 are Xception were also performed well. Therefore, our findings and database can be a helpful resource for the betterment of agriculture.
We tried to apply Ensemble model by combining 3 different models VGG16, ResNet50 and Inception v3 and got separate results of those models but cannot able to carry out the combine result of that Ensemble model. This issue might be solve by using more high performance computer and adding some more classification on data set. While implementing Ensemble, we got faster result of those different models and less execution time than other models. In future research, Ensemble can be used for making the system or getting result more faster and better result than other models. Furthermore an hardware device can be implemented which can be related to classification of soil by observing ph and fertility. That device can be able to present the fertility data from live pictures. As we used a minimum scale of data set of Bangladeshi soil samples from different places of our country. In future gathering more samples from every districts of Bangladesh to make a larger date set which can be created a diversity in results and improve the result of the models. We hope that our work advances current research on a range of important topics as well as on well-liked picture classification and identification challenges. We hope that, our work advances current research on a range of important topics as well as on well-liked picture classification and identification challenges.

Bibliography

[1] J. I. Rivera and C. A. Bonilla, “Predicting soil aggregate stability using readily available soil properties and machine learning techniques,” *Catena*, vol. 187, p. 104 408, 2020.

[2] A. Gholizadeh, L. Borvka, M. Saberioon, and R. Vašát, “A memory-based learning approach as compared to other data mining algorithms for the prediction of soil texture using diffuse reflectance spectra,” *Remote Sensing*, vol. 8, no. 4, p. 341, 2016.

[3] C. Meng, W. Yang, H. Lan, X. Ren, and M. Li, “Development and application of a vehicle-mounted soil texture detector,” *Sensors*, vol. 20, no. 24, p. 7175, 2020.

[4] W. Wu, A.-D. Li, X.-H. He, R. Ma, H.-B. Liu, and J.-K. Lv, “A comparison of support vector machines, artificial neural network and classification tree for identifying soil texture classes in southwest china,” *Computers and Electronics in Agriculture*, vol. 144, pp. 86–93, 2018.

[5] Y. Zhu, D. C. Weindorf, and W. Zhang, “Characterizing soils using a portable x-ray fluorescence spectrometer: 1. soil texture,” *Geoderma*, vol. 167, pp. 167–177, 2011.

[6] Z. Zhao, T. L. Chow, H. W. Rees, Q. Yang, Z. Xing, and F.-R. Meng, “Predict soil texture distributions using an artificial neural network model,” *Computers and electronics in agriculture*, vol. 65, no. 1, pp. 36–48, 2009.

[7] L. Yang, Y. Cai, L. Zhang, M. Guo, A. Li, and C. Zhou, “A deep learning method to predict soil organic carbon content at a regional scale using satellite-based phenology variables,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 102, p. 102 428, 2021.

[8] P. Srivastava, A. Shukla, and A. Bansal, “A comprehensive review on soil classification using deep learning and computer vision techniques,” *Multimedia Tools and Applications*, vol. 80, no. 10, pp. 14 887–14 914, 2021.

[9] H. Abdu, D. Robinson, M. Seyfried, and S. B. Jones, “Geophysical imaging of watershed subsurface patterns and prediction of soil texture and water holding capacity,” *Water resources research*, vol. 44, no. 4, 2008.

[10] V. N. T. Le, S. Ahderom, and K. Alameh, “Performances of the lbp based algorithm over cnn models for detecting crops and weeds with similar morphologies,” *Sensors*, vol. 20, no. 8, p. 2193, 2020.

[11] Y. Cai, W. Zheng, X. Zhang, L. Zhangzhong, and X. Xue, “Research on soil moisture prediction model based on deep learning,” *PloS one*, vol. 14, no. 4, e0214508, 2019.

[12] K. Radhika and D. Madhavi Latha, "Machine learning model for automation of soil texture classification.," *Indian Journal of Agricultural Research*, vol. 53, no. 1, 2019.

[13] R. Swetha, P. Bende, K. Singh, S. Gorthi, A. Biswas, B. Li, D. C. Weindorf, and S. Chakraborty, "Predicting soil texture from smartphone-captured digital images and an application," *Geoderma*, vol. 376, p. 114 562, 2020.

[14] R. Andrade, W. M. Faria, S. H. G. Silva, S. Chakraborty, D. C. Weindorf, L. F. Mesquita, L. R. G. Guilherme, and N. Curi, "Prediction of soil fertility via portable x-ray fluorescence (pxrf) spectrometry and soil texture in the brazilian coastal plains," *Geoderma*, vol. 357, p. 113 960, 2020.

[15] Q. Luan, X. Fang, C. Ye, and Y. Liu, "An integrated service system for agricultural drought monitoring and forecasting and irrigation amount forecasting," in *2015 23rd International Conference on Geoinformatics*, IEEE, 2015, pp. 1–7.

[16] V. H. G. Z. de Andrade, M. Redmile-Gordon, B. H. G. Barbosa, F. D. Andreote, L. F. W. Roesch, and V. S. Pylro, "Artificially intelligent soil quality and health indices for 'next generation'food production systems.," *Trends in Food Science & Technology*, vol. 107, pp. 195–200, 2021.

[17] P. A. de Oliveira Morais, D. M. de Souza, M. T. de Melo Carvalho, B. E. Madari, and A. E. de Oliveira, "Predicting soil texture using image analysis," *Microchemical Journal*, vol. 146, pp. 455–463, 2019.

[18] D. Curcio, G. Ciraolo, F. D'Asaro, and M. Minacapilli, "Prediction of soil texture distributions using vnir-swir reflectance spectroscopy," *Procedia Environmental Sciences*, vol. 19, pp. 494–503, 2013.

[19] R.-M. Yang and W.-W. Guo, "Using time-series sentinel-1 data for soil prediction on invaded coastal wetlands," *Environmental monitoring and assessment*, vol. 191, no. 7, pp. 1–14, 2019.

[20] J. Cao, Z. Zhang, Y. Luo, L. Zhang, J. Zhang, Z. Li, and F. Tao, "Wheat yield predictions at a county and field scale with deep learning, machine learning, and google earth engine," *European Journal of Agronomy*, vol. 123, p. 126 204, 2021.

[21] X. Ding, Z. Zhao, Q. Yang, L. Chen, Q. Tian, X. Li, and F.-R. Meng, "Model prediction of depth-specific soil texture distributions with artificial neural network: A case study in yunfu, a typical area of udults zone, south china," *Computers and electronics in agriculture*, vol. 169, p. 105 217, 2020.

[22] S. S. Yamaç, C. Şeker, and H. Negiş, "Evaluation of machine learning methods to predict soil moisture constants with different combinations of soil input data for calcareous soils in a semi arid area," *Agricultural Water Management*, vol. 234, p. 106 121, 2020.

[23] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artificial Intelligence in Agriculture*, vol. 2, pp. 1–12, 2019.

[24] A. M.-C. Wadoux, "Using deep learning for multivariate mapping of soil with quantified uncertainty," *Geoderma*, vol. 351, pp. 59–70, 2019.

[25] E. Guidang, "Classifying soil texture images using transfer learning," in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, vol. 482, 2019, p. 012 042.

[26] B. Sudarsan, W. Ji, A. Biswas, and V. Adamchuk, "Microscope-based computer vision to characterize soil texture and soil organic matter," *Biosystems Engineering*, vol. 152, pp. 41–50, 2016.

[27] P. A. de Oliveira Morais, D. M. de Souza, B. E. Madari, and A. E. de Oliveira, "A computer-assisted soil texture analysis using digitally scanned images," *Computers and Electronics in Agriculture*, vol. 174, p. 105 435, 2020.

[28] C. Gomez, S. Dharumarajan, J.-B. Féret, P. Lagacherie, L. Ruiz, and M. Sekhar, "Use of sentinel-2 time-series images for classification and uncertainty analysis of inherent biophysical property: Case of soil texture mapping," *Remote Sensing*, vol. 11, no. 5, p. 565, 2019.

[29] P. Vendrame, R. Marchão, D. Brunet, and T. Becquer, "The potential of nir spectroscopy to predict soil texture and mineralogy in cerrado latosols," *European Journal of Soil Science*, vol. 63, no. 5, pp. 743–753, 2012.

[30] C. Hermansen, M. Knadel, P. Moldrup, M. H. Greve, D. Karup, and L. W. de Jonge, "Complete soil texture is accurately predicted by visible near-infrared spectroscopy," *Soil Science Society of America Journal*, vol. 81, no. 4, pp. 758–769, 2017.

[31] C. L. Thomas, J. Hernandez-Allica, S. J. Dunham, S. P. McGrath, and S. M. Haefele, "A comparison of soil texture measurements using mid-infrared spectroscopy (mirs) and laser diffraction analysis (lda) in diverse soils," *Scientific Reports*, vol. 11, no. 1, pp. 1–12, 2021.

[32] J. Padarian, B. Minasny, and A. McBratney, "Using deep learning to predict soil properties from regional spectral data," *Geoderma Regional*, vol. 16, e00198, 2019.

[33] O. Odebiri, J. Odindi, and O. Mutanga, "Basic and deep learning models in remote sensing of soil organic carbon estimation: A brief review," *International Journal of Applied Earth Observation and Geoinformation*, vol. 102, p. 102 389, 2021.

[34] W. H. Ernst, F. Knolle, S. Kratz, and E. Schnug, "Institute of plant nutrition and soil science," 2004.

[35] R. Andrade, S. H. G. Silva, W. M. Faria, G. C. Poggere, J. Z. Barbosa, L. R. G. Guilherme, and N. Curi, "Proximal sensing applied to soil texture prediction and mapping in brazil," *Geoderma Regional*, vol. 23, e00321, 2020.

[36] T. Kattenborn, J. Leitloff, F. Schiefer, and S. Hinz, "Review on convolutional neural networks (cnn) in vegetation remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, pp. 24–49, 2021.

[37] T. N. Abu-Jamie and S. S. Abu-Naser, "Classification of sign-language using vgg16," *International Journal of Academic Engineering Research (IJAER)*, vol. 6, no. 6, 2022.

[38] S. Hershey, S. Chaudhuri, D. P. Ellis, J. F. Gemmeke, A. Jansen, R. C. Moore, M. Plakal, D. Platt, R. A. Saurous, B. Seybold, *et al.*, "Cnn architectures for large-scale audio classification," in *2017 ieee international conference on acoustics, speech and signal processing (icassp)*, IEEE, 2017, pp. 131–135.

[39] T. Subetha, R. Khilar, and M. S. Christo, "A comparative analysis on plant pathology classification using deep learning architecture–resnet and vgg19," *Materials Today: Proceedings*, 2021.

[40] S. M. Sam, K. Kamardin, N. N. A. Sjarif, N. Mohamed, *et al.*, "Offline signature verification using deep learning convolutional neural network (cnn) architectures googlenet inception-v1 and inception-v3," *Procedia Computer Science*, vol. 161, pp. 475–483, 2019.

[41] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1251–1258.

[42] K. Srinivasan, L. Garg, D. Datta, A. A. Alaboudi, N. Jhanjhi, R. Agarwal, and A. G. Thomas, "Performance comparison of deep cnn models for detecting driver's distraction," *CMC-Computers, Materials & Continua*, vol. 68, no. 3, pp. 4109–4124, 2021.