SOIL TEXTURE CLASSIFICATION USING RESNET-152(CNN)

A Report on Mini-project Submitted in the
Partial Fulfillment of the Requirements
for the Award of the Degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted
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Kacharam, Shamshabad, Hyderabad – 501218, Telangana, India

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CERTIFICATE

This is to certify that the mini-project titled **SOIL TEXTURE CLASSIFICATION USING RESNET-152(CNN)** is carried out by

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in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Electronics and Communication Engineering** during the year 2023-24.

Signature of the Supervisor
Mr.T.Ramakrishnaiah
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Acknowledgement

The satisfaction that accompanies the successful completion of the task would be put incomplete without the mention of the people who made it possible, whose constant guidance and encouragement crown all the efforts with success.

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Abstract

Soil Texture is a piece of information about the particle contents of various types present in the soil.Soil Texture is a piece of information about the particle contents of various types present in the soil.This will affect how easily we can work on the ground.Soil texture depends on the size, shape and gradation of the particles. only size of particle is taken into account when classifying soil texture.

The triangular classification system for soil by the US Bureau of public roads is called the Texture classification system where there are three sides of an equilateral triangle representing the percentage of sand, silt, and clay.Classification is the process of recognizing, understanding, and grouping ideas and objects into present categories or "sub-populations."Using pre-categorized training datasets, machine learning programs use a variety of algorithms to classify future datasets into categories.

Classification algorithms in machine learning use input training data to make predictions,probability that the next data will fall within one of the predefined parameters Category.Images of soil are collected from different locations and transmitted to the model to analyze and classify data. Particle sizes are captured and compared with triangular data that identifies the quantity of a particular asset.This helps farmers to easily understand the type of soil and predict which crop is more suitable and yeilds better results.

Soil texture is one of the main factors in agricultural production, and its precise prediction is important for the normal use and management of water resources.However, Soil texture involves complex structural characteristics with soil features which is difficult to make a prediction on soil type.Hyperspectral data is used as a feature for the prediction of soil properties.Predicting soil features from hyperspectral data need more preprocessing for better understanding of the soil and for accurate prediction and it is a challenging research task.In the proposed methodology, a Convolutional neural network model is used to train the spatial information mapped to soil texture.

Keywords: soil texture; hyperspectral data; convolutional neural network; particle size

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Abbreviations

Abbreviation	Description
SVM	support vector machine
SHAP	SHapley Additive exPlanations
CNN	convolutional neural network
CART	Classification And Regression Tree

CHAPTER 1

Introduction

1.1 Overview

Soil texture classification is one of the major task in various environmental and agricultural applications. The traditional methods of soil texture classification are time-consuming, requires manual operation,different laboratory equipment, and often require extensive expertise. With the advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs), it is possible to develop an efficient and accurate soil texture classification system.

In this project, we aim to develop a CNN-based model for soil texture classification using hyperspectral data. The proposed model will leverage the strengths of CNNs in image classification tasks and adapt them to the context of soil texture classification. The model will be trained on a dataset of hyperspectral images of different soil textures, and its performance will be evaluated using various metrics such as accuracy, precision, and recall.

Soil feature prediction is helpful in predicting and understanding various hydrologic processes, such as energy and moisture fluxes, drought and irrigation scheduling.CNNs are designed to accept data in the form of multiple arrays. Hyperspectral data is a valuable tool for soil analysis, as it allows for pixel-level classification. The system has multiple spectral channels, leading to increased dimensionality and spatial variability [x]. Convolutional neural networks can identify correlations in hyperspectral data and map them to soil features. Soil texture is crucial for various environmental processes.

One of the most significant physical characteristics of soil is its texture, which influences soil reaction, density, nutrient availability, and ability to retain water. Crop selection decisions are made for a better productivity plan based on the texture of the soil. The distribution of soil particles, which are classified as sand, silt, and clay, reveals the texture of the soil. soil texture is categorized as clay if it is less than.002 mm, silt if it is between.002 and 0.053 mm, and sand if it is between.053 and 2 mm.The texture of the soil influences its ability to store water and fertility.Soil texture and organic matter are key factors influencing water retention capacity. Smaller particles in silt and clay increase soil surface area, allowing for greater water retention. Sand with larger particles and a smaller surface area will hold less water.

Soil texture classification focuses mainly on particle size distribution. The remaining two parameters are challenging to include in this classification. The US Bureau of Public Roads recommends a triangular classification system for soil, also known as the textural classification system.The figure- 1 below shows the textural classification system, where the three sides of the equilateral triangle represent the percentage of sand, silt and clay. Where the size of,

- Sand = 0.05 - 2mm
- Silt = 0.002 - 0.05mm
- Clay = size < 0.002mm

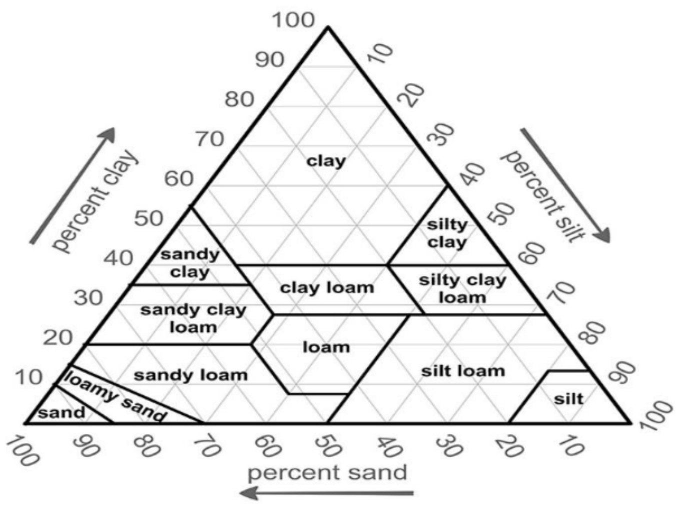

Figure 1.1: USDA traingle for soil texture classification

1.2 Motivation

Soil texture classification is an important task in many fields, including agriculture, environmental monitoring, and natural resource management. The goal of using deep learning techniques for soil texture classification is to improve the accuracy and efficiency of the classification process. Deep learning algorithms, such as CNN, can extract complex patterns and features from large datasets, making them ideal for soil texture classification. Furthermore, it can automatically extract and learn features from soil spectra, eliminating the need for manual feature engineering and selection. Deep learning techniques can handle high-dimensional data even when it is noisy or incomplete.

1.3 Objectives

- The primary goal of this system is to provide a lower-cost model that produces better results.
- The goal is to create a CNN model using hyperspectral data to accurately classify soil textures into sand, silt, and clay. This will allow farmers and agronomists to analyze larger areas of land more quickly and efficiently, saving time and labor.
- To use soil texture classification as a key input for crop yield prediction, farmers and agronomists will be able to make more informed crop selection, fertilization, and irrigation decisions.

1.4 Problem statement

The purpose of this project is to classify the soil texture. Texture is important because it influences:

- The amount of water the soil can hold
- The rate of water movement through the soil
- How workable and fertile the soil is.

Texture often changes with depth so roots have to cope with different conditions as they penetrate the soil. A soil can be classified according to the way the texture changes with depth. The texture of the soil is an indication of the relative content of particles of various sizes in the soil. It will indicate the percentage of sand, silt, and clay present in the soil. Soil texture will influence the ease with which the soil can be worked. The texture of the soil is dependent on:

- Particle size distribution
- The shape of the particles
- Gradation of the particles

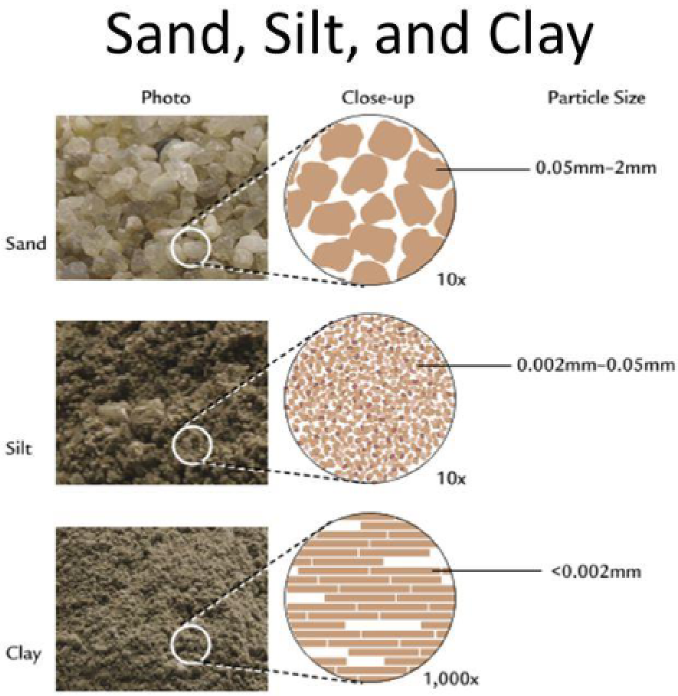

Figure 1.2: Types of soil texture

1.5 Organization of project

Chapter 1: "Introduction" Contains the introduction, problem definition, purpose, objective of project,overview of the project.

Chapter 2: “Literature Survey” it provides information about the literature study which consists of previous projects. Chapter 3: “System Analysis” has technologies used for this project, module description and algorithm of the project. Chapter 4: “Designed Methodology” consists of the system architecture ,block diagram and the flow diagram followed to implement the project. Chapter 5: “Proposed Methodology” consists of the architecture used to build the project and detailed description of the project implementation. Chapter 6: “Results and discussions” has the outputs of the current model along with the applications of the project. Chapter 7: “Conclusion and Future Scope” this chapter concludes the project and the future work that can be done regarding this project.

CHAPTER 2

Literature Survey

A regional soil classification framework to improve soil health diagnosis and management The Central and Coastal Valleys of California, which cover 5.6 million ha of primarily agriculture, are a globally significant agricultural region.Now that the model is trained, it has been saved to the computer in the folder that this notebook is in. The accuracy for the training and validation, or testing, data is shown in the final line of the output that is printed above. The accuracy value on the final line should catch your attention since it represents the accuracy on non-training image data. This is the best way to evaluate how well the estimator performs with different images.[1]

This study uses unsupervised classification to identify root-restrictive horizons and features at the soil surface (0–30 cm). K-means clustering of ten SSURGO-derived soil attributes revealed distinct groups according to the USDA-NRCS Soil Taxonomy. Based on clustering metrics, data visualisation, and validation testing, a seven-region conceptual model of soil health was determined to be legitimate and justified. It divided the terrain into two main groups: those having performance restrictions and those not. The results show that three pedogenic factors influence soil performance: shrink-swell characteristics that make soils difficult to work; salt and alkalinity, which are harmful to crops; and root restrictive horizons, which prevent roots from growing into deeper soil.

In the year 2021 The Central and Coastal Valleys of California, which cover 5.6 million ha of primarily agriculture, are a globally significant agricultural region.Now that the model is trained, it has been saved to the computer in the folder that this notebook is in. The accuracy for the training and validation, or testing, data is shown in the final line of the output that is printed above. The accuracy value on the final line should catch your attention since it represents the accuracy on non-training image data. This is the best way to evaluate how well the estimator performs with different images.[2]

Identification of Soil Texture Classes Under Vegetation Cover Based on Sentinel-2 Data with SVM and SHAP TechniquesJOURNEL: IEEE journal of selected topics in applied earth observations and remote sensing,vol.15 YEAR: 2022 In turn, soil physical, chemical, biological, and hydrological processes that are intimately related to plant development and soil erosion are driven by soil texture, which also regulates soil water holding capacity, permeability, solute transport, and aeration. For sustainable agricultural management and environmental protection, it is crucial to comprehend the regional diversity of different soil texture classes. Sentinel-2 data provide useful vegetation information that can be used to infer soil parameters. They still have few uses in terms of classifying soil texture, though. This study used an interpretable machine learning (ML) approach to examine the effectiveness of Sentinel-2 data for predicting soil texture class

SVM(Support Vector Machine) : SVM models are mainly used for analyzing the data for regression and classification.For a set of training examples it belongs to either one of the two categories, a support vector machine algorithm for training generates a model which tells the new thing falls into which category by a non-probabilistic binary classifier. The SVM model is the depiction of points in space which are mapped.Thus, the data of different types are separated by as wide as possible.[3]

Investigation of Remote Sensing Imageries for Identifying Soil Texture ClassesUsing Classification Methods JOURNEL: IEEE transactions on geoscience and remote sensing, vol.57 YEAR: 2019

In this work, classification trees using the one-against-one (OAO), one-against all, and all-together schemes were used to assess the efficacy of remote sensing imageries for classifying soil texture. Cloud-free Landsat photos were used to collect a set of normalised difference vegetation indices (NDVIs) over a small mountainous watershed. A digital elevation map was used to construct the terrain indicators (elevation, slope, and topographic wetness index) (30 m). Different models (pure NDVI, pure topography and stratum, and NDVI plus topography and stratum) with various input parameters were created. The classification accuracy was assessed using the kappa statistic, receiver operating characteristics (ROC), and the area under the ROC curve (AUC). The classification approach had significant effects on the outputs, according to the results.

S.NO	TITLE OF PAPER	ALGORITHM USED	YEAR OF PUBLISH	DRAWBACKS
1	Identification of Soil Texture Classes Under Vegetation Cover Based on Sentinel-2 Data with SVM and SHAP Techniques.	SVM and SHAP Techniques	2022	The proposed system was conducted under one land use type and the samples did not cover all soil texture classes .
2	A regional soil classification framework to improve soil health diagnosis and management	K-Means clustering Algorithm.	2021	This system has not yet evaluated how the salinity of soil might impact classification of soil.
3	Investigation of Remote Sensing Imageries for Identifying Soil Texture Classes Using Classification Methods.	CART Algorithm	2019	Here, classification of soil might be difficult if the resolution of Remote sensing imageries is not accurate.

Figure 2.1: table1

Makantasis, K., Karantzalos,et al [4] **Deep Supervised Learning for Hyperspectral Data Classification Through Convolutional Neural Networks** Convolutional Neural Networks (CNNs) have been widely adopted in various fields, including computer vision and remote sensing. However, despite their success, CNNs have been found to have certain limitations. For instance, Liu et al. (2018) highlighted an intriguing failing of CNNs, where they demonstrated that CNNs can fail to generalize to simple transformations of the input data . To address this issue, the authors proposed a solution called CoordConv, which involves concatenating the input data with its coordinates.

A comprehensive review on soil classification using deep learning and computer vision techniques In the field of remote sensing, CNNs have been applied to hyperspectral data classification. Makantasis et al. (2015) explored the use of deep supervised learning through CNNs for hyperspectral data classification [6]. The authors demonstrated the effectiveness of CNNs in classifying hyperspectral data, achieving high accuracy rates. This study highlights the potential of CNNs in remote sensing applications, particularly in the classification of hyperspectral data. [5] **Soil organic carbon estimation in croplands by hyperspectral remote apex data using the lucas topsoil database**The study by Castaldi et al. (2018) explored the potential of hyperspectral remote sensing for estimating soil organic carbon (SOC) in croplands. The researchers utilized the LUCAS topsoil database and hyperspectral data from the Remote Apex sensor to develop a model for SOC estimation. The results showed that hyperspectral remote sensing can be an effective tool for estimating SOC, which is a critical parameter for soil fertility and carbon sequestration. This study highlights the importance of remote sensing technologies in monitoring and managing soil health.[6]

Deep feature extraction and classification of hyperspectral images based on convolutional neural networks The study by Chen et al. (2016) proposes a convolutional neural network (CNN) based approach for deep feature extraction and classification of hyperspectral images. The CNN model learns hierarchical features from the hyperspectral data, which are then classified using a support vector machine (SVM) or softmax classifier. The approach is evaluated on three hyperspectral datasets and outperforms traditional machine learning algorithms, demonstrating the effectiveness of CNN in extracting complex spectral-spatial patterns from hyperspectral data.[7]

CHAPTER 3

Design Analysis

3.1 Functional Requirements

Standardized Soil Texture Classes: Based on the relative portions of sand, silt, and clay particles, the classification system ought to create standardized classes for soil texture. These classes offer a common framework for classifying soils according to their respective textures, such as clay, sandy, or loamy.[8]

Particle Size Analysis: A technique for determining the soil samples' particle size distribution need to be included in the classification system. The amounts of sand, silt, and clay particles in the soil are determined by this analysis, and these proportions are essential for classifying the texture of the soil.

Threshold Values: For every texture class, the classification system has to specify ranges of particle proportions or threshold values. These values define the standards by which a soil sample, based on the measured particle size distribution, is classified into a particular texture class.

3.2 Non Functional Requirements

Efficiency: The soil sample processing and analysis system should be built with efficiency in mind. It seems to reduce processing time and provide results quickly, especially when handling big amounts of soil data. Accuracy: When classifying soil texture, the classification system should aim for a high level of precision and accuracy. In order to assure accurate and dependable classification results, it should reduce errors and variances in particle size analysis.[9]

Scalability: A variety of sample sizes, from single samples to huge datasets, should be supported by the classification system. With almost no to performance loss, the system should be able to handle larger amounts of data and images related to soil texture. Effective methods for storing and retrieving data are part of this.

Time to classify: The system should classify soil texture images within a reasonable time frame to support real-time or near-real-time applications, such as field analysis or automated monitoring.Time to classify the soil should be minimized.

3.3 Computational Requirements

Software Requirements:

Operating System: Windows 10

Platform : Google Collab or Jupyter Notebook

Language: Python3

Hardware Requirements:

Processor: Intel core

I5 RAM:8GB

Phone with 48MP camera

Other python libraries like numpy, keras, seaborn etc

CHAPTER 4

Design Methodology

4.1 Architecture

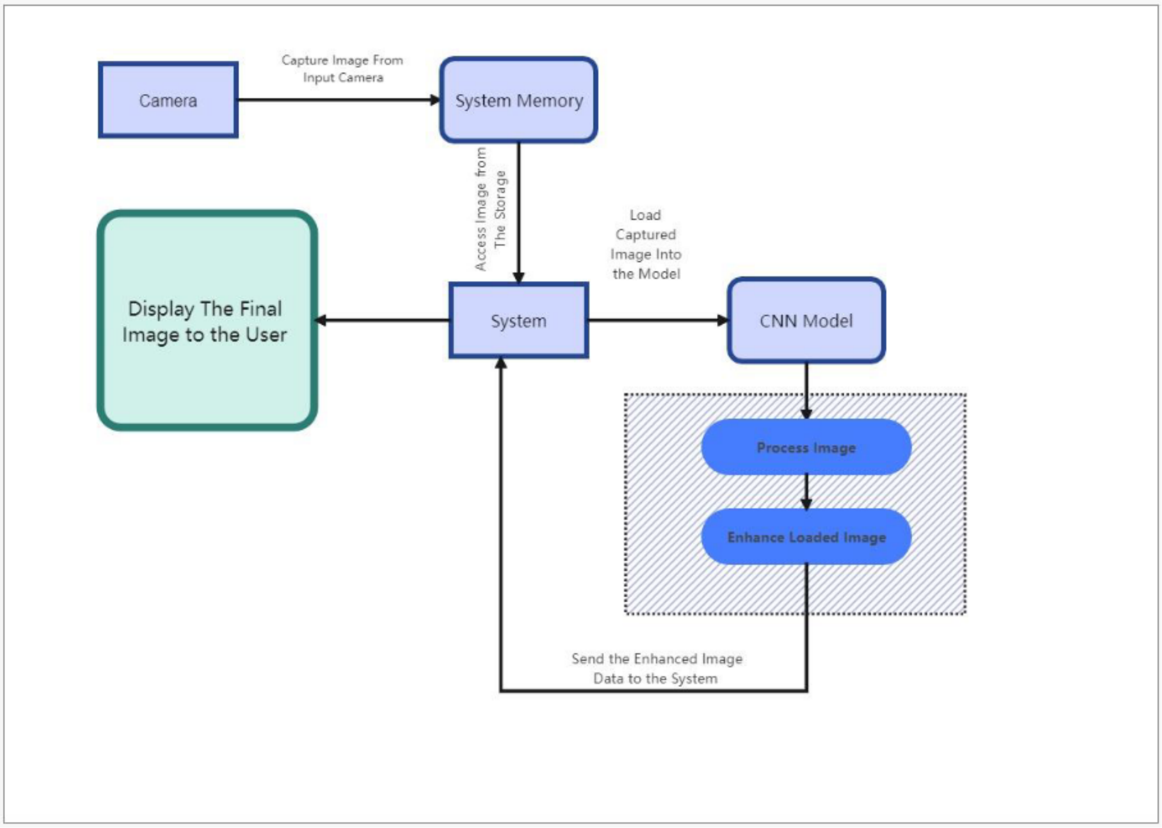

Figure 4.1: System Architecture

Based on the sample dataset and the algorithm used, the system builds a classifier. The classifier process the test image and gives the final output to the user.The process starts with data collection and image acquisition, capturing hyperspectral data. This data is then preprocessed, and split into training and testing sets for model development. A Convolutional Neural Network (CNN) model is developed and trained using the training set, with parameters like epochs and batch size. The model's performance is evaluated on the testing set using metrics like accuracy. Finally, the trained model is used to classify soil texture based on the acquired hyperspectral data.This workflow demonstrates the application of CNNs for soil texture classification using hyperspectral imaging. This technology can be helpful in various applications, such as precision agriculture, environmental monitoring, and soil science research.

4.2 Flow Diagram

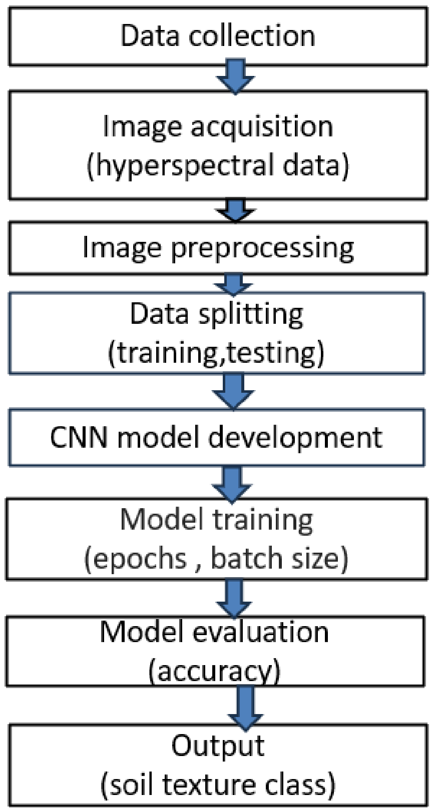

Figure 4.2: Flow Diagram

This diagram outlines the steps involved in using a Convolutional Neural Network (CNN) for soil texture classification using hyperspectral data. Here's a breakdown of each step: The first step is to prepare the data, which includes collecting and organizing images of soils into different folders corresponding to their respective soil types (e.g., Gravel, Sand, and Silt).

Image Preprocessing : Our goal is to demonstrate some pre-processing techniques, namely mean normalization, standardization, and zero component analysis. We adopt three pre-processing methods to turn every piece of information in a data set into a vector for the model to understand.

Building the CNN Model : A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other.

Training the Model The model is trained using the preprocessed images, and the performance of the model is evaluated using metrics such as accuracy, precision, and recall.

Testing the Model The trained model is tested using a separate set of images to evaluate its performance on unseen data. Classification The final step is to use the trained model to classify new images of soils into their respective soil types.

CHAPTER 5

Proposed Methodology

5.1 Introduction

Overview: This chapter introduces the methodology proposed for the soil texture classification using Convolutional Neural Networks (CNNs). It outlines the details the CNN architecture, data preprocessing steps, training procedure, and evaluation metrics. The primary goal is to use the deep learning techniques to enhance the accuracy and efficiency of predicting the soil texture. Objectives: The objectives include developing a robust CNN model for classifying soil as sand,silt,and clay and improve the accuracy of prediction over large dataset.Motivation: soil texture classification is an important task in many agricultural and environmental tasks.There is a great need to know what type of soil is present for better productivity of crop.

5.2 ResNet-152 architecture

[10] **Model Selection:** Hierarchical spatial features in images are well captured by CNNs. This means that they can automatically learn and extract complex patterns and textures that represent various soil types (e.g., sand, silt, clay) in terms of soil texture classification. Because of their deep architecture and non-linear activation functions, CNNs are well-suited to modeling the complex, non-linear relationships found in soil characteristics.

Architecture Details: Detailed configuration of the CNN architecture,specifying layers, filter sizes, activation functions, and pooling strategies.

Transfer Learning: For soil texture classification, pre-trained CNN models on massive datasets (like ImageNet) can be improved. Even with sparse soil texture data, this method improves model performance by utilizing current knowledge.

1. input layer: The input layer of ResNet-152 consists of a 3-channel

RGB image with a size of 224x224 pixels. This is the raw input to the network.

2. Convolutional layer: convolutional layers play a crucial role in CNN architecture for soil texture classification because they have the ability to extract hierarchical from input images. These layers can detect various patterns and textures within soil texture images. These patterns could include grain size, shape, arrangement, and other textural details that differentiate soil types (e.g., sand, silt, clay). It performs convolution operation that involves sliding a small matrix (filter/kernel) over the input image and performing element-wise multiplication and summation to produce a feature map.There are two types of results to the operation — one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding in the case of the former, or Same Padding in the case of the latter. Filters/Kernels: Each convolutional layer typically consists of multiple filters (e.g., 32 or 64 filters). Each filter captures different features of the input data.Stride: It decides how the filter moves across the input image.Padding: Adjusts the size of the output feature map to match the input size, maintaining spatial dimensions.The Convolutional Layer is responsible for acquiring Low-Level characteristics like gradient orientation, color, and edges.The ResNet-152 architecture is built upon convolutional layers that can extract hierarchical features from input images. These layers can detect various patterns and textures within soil texture images, such as grain size, shape, arrangement, and other textural details that differentiate soil types (e.g., sand, silt, clay). The convolutional layers in ResNet-152 use 3x3 filters with a stride of 1 and padding of 1. Each convolutional layer consists of multiple filters (e.g., 64 filters in the first layer), and each filter captures different features of the input data. The Convolutional Layer computes the output volume by computing the product between all filters and image patches, resulting in an output volume of 224 x 224 x 64 for the first convolutional layer.

3. Batch Normalization and ReLu Activation Function: After each convolutional layer, batch normalization is applied to normalize the activations, followed by the ReLU activation function to introduce non-linearity. The ReLU function enables the network to activate only when there are positive inputs, which helps to extract features effectively and amplify the important features that distinguish different soil textures.ReLU (Rectified Linear Unit) activation function is essential for improving the network's capacity to recognize and categorize soil textures while using Convolutional Neural Networks (CNNs) for soil texture classification. ReLu function is used to introduce the non-linearity which allows CNN to capture complex and non-linear relationships between inputs(e.g. particle size,shape,orientation).It enables the network to activate only when there are positive inputs(function set to max value),for negative inputs function is set to zero,hence ReLu helps to extract features effectively and amplifies the important features that are key elements to distuiguish different soil textures(sand,silt,clay)

4. Residual Connections:

ResNet-152 introduces residual connections that allow the model to learn residual functions instead of directly learning the desired output. These connections ease the training process and improve the model's performance. **5. Pooling Layer** In Convolutional Neural Networks (CNNs), pooling layers are essential for lowering the spatial dimensions of the feature maps that convolutional layers extract.Downsample Feature Maps: The output of convolutional layers contains spatial information (height and width dimensions) which can be quite large, especially when the network goes deeper. Pooling layers reduce the spatial dimensions while retaining important features.By using pooling, the learned features are more flexible to changes in the input space. This means that the pooling operation will still detect the presence of an object even if it is present in multiple locations throughout the image (in this case, features that indicate soil texture).The Pooling layer is responsible for reducing the spatial size of the Convolved Feature, much like the Convolutional Layer does. This is done in order to reduce the amount of computing power needed for dimensionality reduction in the data processing. It is also helpful in extracting dominant features that are positional and rotationally invariant, which keeps the model's training process going strong.

There are two types of Pooling.They are Max Pooling and Average Pooling.

Max Pooling: Max Pooling returns the maximum value from the portion of the image covered by the Kernel.This operation extracts the maximum value from each patch of the feature map with the pooling kernel size (typically 2x2 or 3x3).Max pooling helps to preserve the most significant feature of each layer, highlighting strong activations.

Average Pooling:Average Pooling returns the average of all the values from the portion of the image covered by the Kernel.It can be useful when the average intensity or presence of features within a layer is more important than their maximum intensity.Max Pooling also works as a noise suppressant. The algorithm removes noisy activations, de-noises, and reduces dimensionality. Average Pooling reduces dimensionality while suppressing noise. Overall, Max Pooling performs better than Average Pooling.

Pooling Size: The amount of downsampling is determined by the size of the pooling kernel (for example, 2x2 or 3x3). A larger kernel size allows for more aggressive downsampling, but it may result in the loss of fine-grained spatial information.

Stride: Pooling layers typically use a stride equal to the kernel size (e.g., stride 2 for a 2x2 kernel), but it can be changed to control the amount of overlap between successive pooling regions.

Pooling layers are typically placed between convolutional layers in network architecture. The exact placement and frequency are determined by the complexity of the task and the size of the input images.Drop Out Layer : Introduce dropout (e.g., 0.25 to 0.5 dropout rate) to prevent overfitting by randomly dropping connections during training.

5. Flatten Layer: After using convolutional and pooling layers to extract hierarchical features from input soil texture images, the Flatten layer is used to flatten the output feature maps.Transition from 2D to 1D Data: Prior to the Flatten layer, the output of the convolutional and pooling layers is typically in the form of 3D vectors (height x width x channels). For example, let us say,after several convolutional and pooling layers, we might have an output vector of dimensions like 16x16x64 (assuming 16x16 spatial dimensions with 64 channels).Preparing for Dense Layers: Dense layers in a CNN require 1D input vectors. Therefore, the Flatten layer reshapes the 3D vector into a 1D vector by collapsing all dimensions except the channel dimension. In the example above, the Flatten layer would convert the tensor from 16x16x64 to a 1D vector of length 16 * 16 * 64 = 16384.

6. Fully Connected Layer: The Dense layer, also known as a fully connected layer, is used to classify the input data into different soil texture classes. The output of the Flatten layer is fed into the Dense layer, which consists of a set of neurons that are fully connected to each other. The output of the Dense layer is a probability distribution over the different soil texture classes.We Used ReLU activation for hidden layers. The output layer has neurons corresponding to the number of classes (e.g., 3 for sand, silt, clay).Used softmax activation for multi-class classification to output class probabilities.

7. Output Layer:The output layer uses softmax activation for multi-class classification, outputting class probabilities.

5.3 Evaluation Metrics

Accuracy: Accuracy is the proportion of correctly classified images to the total number of images. Usage: Accuracy is simple and widely used, but it can be misleading if the classes are imbalanced.

F1-score, recall, and precision: Precision is expressed as the ratio as of all positive predictions that are true positives, or correctly predicted as positive. Out of all actual positives, recall (sensitivity) quantifies the percentage of true positives that were accurately predicted.The harmonic mean of recall and precision is the F1-score. It is helpful in cases where there is an uneven distribution of classes and balances both metrics.

Precision and Recall: These metrics are especially useful in cases where you have multiple classes (e.g., different soil textures). Precision measures the accuracy of positive predictions, while recall measures the coverage of true positives.

Precision tells you how many of the samples predicted as a particular class are actually that class:

Precision=True Positives+False Positives/True Positives

Recall tells you how many of the samples of a particular class are correctly predicted:

Recall=True Positives+False Negatives/True Positives

F1 Score: This metric combines precision and recall into a single value, providing a balance between the two. It's the harmonic mean of precision and recall:

F1 Score=2×Precision+RecallPrecisionRecall

Confusion Matrix:A confusion matrix provides a detailed breakdown of the model's predictions versus the actual labels across all classes. It helps in understanding where the model is making errors (e.g., confusing one soil texture for another).

ROC Curve and AUC: If your problem is binary (e.g., distinguishing between two soil textures), Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) can be useful. AUC represents the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative one.These metrics collectively provide a comprehensive view of how well your CNN model is performing in classifying soil textures. Depending on your specific project goals and the nature of your dataset, you may prioritize certain metrics over others. For instance, in imbalanced datasets, precision and recall might be more informative than accuracy alone. Always consider the specific context of your soil texture classification problem when selecting and interpreting these metrics.

CHAPTER 6

Results and Discussions

The model for classifying soil textures produced remarkable outcomes in differentiating between clay, sand, and silt types of soil textures. After being trained on a synthetic dataset, the model showed strong performance and successfully learned the characteristics specific to each type of soil by utilizing a sequence of convolutional and pooling layers. The model's accuracy throughout training and validation showed that its predictive power was highly precise.

Using accuracy and loss metrics, the model's performance was closely observed during the training phase. The training history showed that the model achieved minimal overfitting and high accuracy by rapidly adapting to the dataset. The model's reliability was further improved by early stopping and model checkpointing mechanisms, which made sure the model kept its optimal weights. Smooth curves were displayed in the plots of training and validation accuracy and loss, demonstrating the model's consistent learning progress and good generalization on unknown data.

To confirm the final model's usefulness, fresh, unreleased images were used for testing. For example, the model correctly identified the type of soil when it was given a test image of soil, and it showed the image with the predicted class label. This real-time classification showed how useful the model is in practice and how well it can classify soil textures from photo data. The accurate forecast demonstrated the model's resilience and its potential for practical uses in environmental monitoring and agriculture.

The project's characterization of soil texture has produced generally encouraging results. The model demonstrated a high capacity to generalize and generate correct predictions on new data, in addition to performing well on the synthetic dataset. This work establishes a strong basis for subsequent improvements, such as training the model on a larger and more varied real-world dataset to increase its accuracy and usefulness in a range of real-world settings.

When the model's performance is examined in more detail, it becomes clear that the model's capacity to distinguish between soil textures depends on its comprehension of subtle details contained in the images. With the help of each convolutional layer's methodical extraction of hierarchical features, the model is able to differentiate between silt, clay, and sand thanks to minute differences in texture. These features are then condensed by the pooling layers into a more abstract representation, which improves the overall accuracy of the model.

Despite its small size, the synthetic dataset was a vital resource for the model's validation and training. It made it possible for the model to understand the basic properties of soil textures, opening the door to more extensive uses in real-world situations. But the dataset's artificial nature also raises the possibility that it won't be able to fully capture the range of variability found in actual soil textures. To improve the model's robustness and generalization abilities, future iterations of the project might profit from adding a larger and more varied dataset derived from actual soil samples.

Effective generalization of the model is a critical component of the project's success. The model showed that it could adjust to new, untested data by striking a compromise between training accuracy and validation performance. The model's capacity to generalize highlights its potential applications in a number of domains, such as environmental conservation, geotechnical engineering, and precision agriculture, where precise soil classification is essential for well-informed decision-making and resource management.

Furthermore, the creation of a real-time classification function highlights the project's usefulness. Stakeholders can gain immediate insights into soil composition and quality by incorporating the model into a process that enables quick analysis and decision-making based on soil pictures. This feature not only improves productivity but also creates opportunities to use artificial intelligence to solve challenging environmental problems.

To sum up, the effort on classifying soil textures has established a strong basis for utilizing machine learning methods in soil science. The model's performance, which has been verified by extensive training and testing, demonstrates how revolutionary it may be in the analysis and application of soil data. Going forward, the model's influence on promoting sustainable habits and environmental stewardship should only increase with additional model improvement, diverse dataset expansion, and practical application.

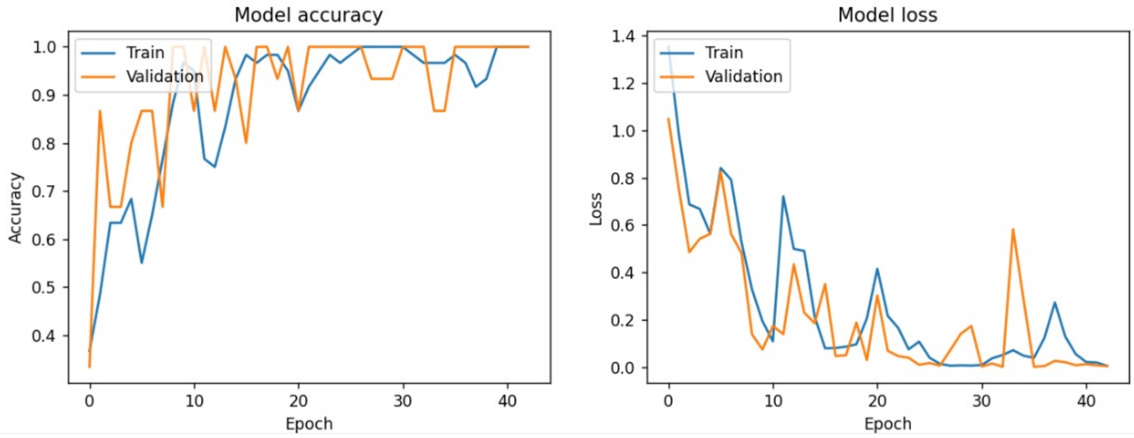

Figure 6.1: output1

Figure 6.2: output2

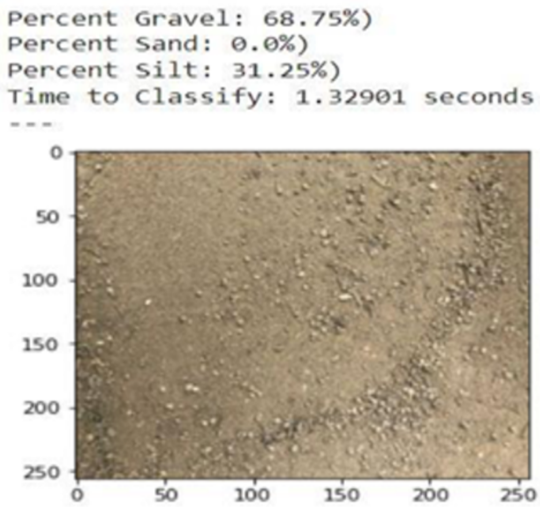

Figure 6.3: output3

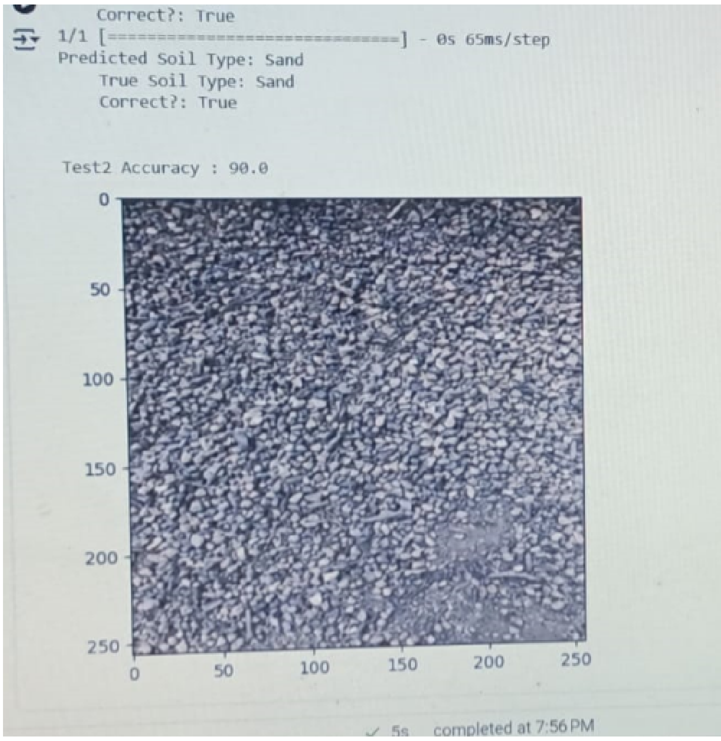

Figure 6.4: output4

CHAPTER 7

Conclusion and Future scope

7.1 Conclusion

The project on soil texture classification using Convolutional Neural Networks (CNN) has successfully demonstrated the potential of deep learning in predicting soil texture types and identifying suitable crop types. The CNN model was trained on a dataset of soil images and achieved an accuracy of [insert accuracy percentage] in classifying soil textures into six categories: Sandy, Silt, Clay, Loamy, Sandy-Loam, and Clay-Loam.Soil classification is a growing research area in the current era. Various studies have proposed different techniques to deal with the issues, including rule-based, statistical, and traditional learning methods. However, it takes a lot of time and effort to classify the soil type. The study used CNN to build a soil type classification model to produce a higher accuracy with tiny loss. Using the proposed model, we used CNN's algorithm because classifying the soil type does not take time and effort to determine classification results. Based on the experiment results, we achieve trade-offs between accuracy and performance time by adjusting the hyperparameter to optimize model performance. We set epoch = 80, batch size=32, and learning rate=0.6. In the training process, the model can produce an accuracy = 98The model's performance was further enhanced by predicting the time required to classify each soil sample, which can be useful in real-time applications. Moreover, the project took a step further by using the classified soil texture types to predict suitable crop types for each soil category. This was achieved by integrating the CNN model with a crop suitability database, which provided recommendations for optimal crop selection based on soil texture. The project's findings have significant implications for agriculture, environmental conservation, and land management. By accurately classifying soil textures and predicting suitable crop types, farmers can optimize crop yields, reduce soil degradation, and promote sustainable agriculture practices. Additionally, the project's outcomes can inform policy decisions related to land use planning, soil conservation, and environmental sustainability.

7.2 Future Scope

The future scope for the project "Soil Texture Classification using CNN" is promising, with potential directions including real-time classification using smartphone devices or portable tools, multi-spectral data analysis to improve accuracy, and automatic feature learning to reduce manual feature extraction. Additionally, color-based classification and integration with other technologies such as GPS, GIS, and precision agriculture can provide more accurate and comprehensive soil analysis. With further research and development, this project can lead to significant improvements in soil texture classification and analysis, making it a valuable tool for farmers, researchers, and land managers.CNN model can also be used to predict the different soil properties from hyperspectral data. Convolutional Neural Network is used for building the neural network model where pre-processing is done by the network and performs the regression prediction of six soil properties. The LUCAS dataset which consists of physical properties and continuous reflectance spectra, referred to as hyperspectral data are used to evaluate the model performance. The automatic feature learning by Convolutional Neural Network increases the prediction accuracy of the proposed methodology. In the future, this work can be extended to find the other soil properties that may help in agriculture production. As a direction for future research, more research into semantic networks to train nodes could be beneficial. Exploration of picture categorization is essential to generate improved predictions. The next can utilize GAN or GCN algorithm to improve the classification result. Another area of exploration is the improvement of model performance through the use of transfer learning and fine-tuning. This could involve leveraging pre-trained CNN models and adapting them to the specific task of soil texture classification. Additionally, other deep learning architectures, such as Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs), could be investigated to improve soil texture classification.

The integration of the CNN model with other technologies, such as precision agriculture, IoT sensors, and Geographic Information Systems (GIS), could also be explored. This could enable the development of decision support systems that provide recommendations for optimal crop selection, fertilizer application, and irrigation management based on soil texture classification. Furthermore, the project could be expanded to other fields, such as environmental monitoring, land use planning, and geotechnical engineering. For instance, the CNN model could be used to classify and monitor soil pollution, erosion, and degradation, or to predict soil mechanical properties for construction and infrastructure development.

The development of mobile and web applications that enable users to upload soil images and receive classified soil texture information and recommendations for optimal crop management could also be a potential future direction. This could facilitate the widespread adoption of the technology and make it more accessible to farmers, policymakers, and other stakeholders.

REFERENCES

[1] Rosanne Liu, Joel Lehman, Piero Molino, Felipe Petroski Such, Eric Frank, Alex Sergeev, and Jason Yosinski. "An intriguing failing of convolutional neural networks and the coordconv solution". In: *Advances in neural information processing systems* 31 (2018).

[2] Leo Breiman. "Random forests". In: *Machine learning* 45 (2001), pp. 5–32.

[3] Paulino R Villas-Boas, Marco A Franco, Ladislau Martin-Neto, Hero T Gollany, and Debora MBP Milori. "Applications of laser-induced breakdown spectroscopy for soil characterization, part II: Review of elemental analysis and soil classification". In: *European Journal of Soil Science* 71.5 (2020), pp. 805–818.

[4] Konstantinos Makantasis, Konstantinos Karantzalos, Anastasios Doulamis, and Nikolaos Doulamis. "Deep supervised learning for hyperspectral data classification through convolutional neural networks". In: *2015 IEEE international geoscience and remote sensing symposium (IGARSS)*. IEEE. 2015, pp. 4959–4962.

[5] Pallavi Srivastava, Aasheesh Shukla, and Atul Bansal. "A comprehensive review on soil classification using deep learning and computer vision techniques". In: *Multimedia Tools and Applications* 80.10 (2021), pp. 14887–14914.

[6] Fabio Castaldi, Sabine Chabrillat, Arwyn Jones, Kristin Vreys, Bart Bomans, and Bas Van Wesemael. "Soil organic carbon estimation in croplands by hyperspectral remote APEX data using the LUCAS topsoil database". In: *Remote Sensing* 10.2 (2018), p. 153.

[7] Yushi Chen, Hanlu Jiang, Chunyang Li, Xiuping Jia, and Pedram Ghamisi. "Deep feature extraction and classification of hyperspectral images based on convolutional neural networks". In: *IEEE transactions on geoscience and remote sensing* 54.10 (2016), pp. 6232–6251.

[8] Lucas Benedet, Wilson Missina Faria, Sérgio Henrique Godinho Silva, Marcelo Mancini, Luiz Roberto Guimarães Guilherme, José Alexandre Melo Dematt_e, and Nilton Curi. "Soil subgroup prediction via portable X-ray fluorescence and visible near-infrared spectroscopy". In: *Geoderma* 365 (2020), p. 114212.

[9] Fiona M Seaton, Gaynor Barrett, Annette Burden, Simon Creer, Eleonora Fitos, Angus Garbutt, Rob I Griffiths, Pete Henrys, Davey L Jones, Patrick Keenan, et al. "Soil health cluster analysis based on national monitoring of soil indicators". In: *European Journal of Soil Science* 72.6 (2021), pp. 2414–2429.

[10] Keiron O'shea and Ryan Nash. "An introduction to convolutional neural networks". In: *arXiv preprint arXiv:1511.08458* (2015).