

# Determining Soil Texture and Its Type Classification Based on Analytical Information and Processing with Integrated Crop Disease Detection

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**Abstract** - The texture of the soil is crucial in determining its ability to retain water, the availability of nutrients, and the overall productivity of agricultural land. Simultaneously, early detection of crop diseases is vital to minimize yield loss and ensure healthy crop growth. This paper presents a dual- approach system that determines soil texture types based on analytical data processing and integrates an image-based crop disease detection model. The soil classification module uses physical and chemical parameters such as sand, silt, and clay percentages to determine the soil type using a texture triangle. Convolutional neural networks (CNNs) and image processing are used to identify plant diseases in leaf photos. By offering real-time insights to improve decision-making, the proposed system seeks to support agronomists and farmers. The model's potential for practical agricultural applications is demonstrated by experimental results, which show that it achieves high accuracy in both soil classification and disease recognition.

**Keywords:** Soil Texture, Soil Classification, Crop Disease Detection, CNN, Image Processing, Precision Agriculture, Smart Farming, Deep Learning, Soil Analysis, Sustainable Agriculture

## I. INTRODUCTION

Agriculture is a pillar of human society and an important industry in the world economy. It is shaped by various factors, among which soil quality and plant health are two of the most significant ones. Soil The proportions of sand, silt, and clay make up texture, which is crucial for root development, nutrient uptake, and water retention growth of plants. Determining and classifying soil texture is crucial to suggesting appropriate crops and optimizing irrigation and fertilization management.

Crop diseases, on the other hand, represent a critical risk to food security and farmers' livelihoods. Manual disease identification is frequently inefficient and unreliable because different diseases may appear visually similar to each other and due to environmental variability. The availability of machine learning and image processing technologies has created the opportunity to design more precise and effective plant disease detection systems.

This work suggests a dual-purpose system that does both soil texture classification and crop disease identification. The

method is based on analyzing soil composition data to classify texture and applying deep learning for disease identification from plant leaf images. The integration is designed to provide a complete solution to enable contemporary precision agriculture, improve decision- making, and help make farming more sustainable The suggested system uses sophisticated algorithms and sensor data to provide farmers with precise, real-time insights. It allows for customized interventions that optimize crop yield and reduce resource waste by fusing soil analysis.



Fig .1. Samples of the nine Soil dataset categories

## II. RELATED WORK

Understanding soil texture is fundamental in agriculture because it directly influences critical factors such as water retention, nutrient availability, root penetration, and overall soil fertility. Traditionally, soil texture is determined through laboratory-based physical methods such as the hydrometer method, sieve analysis, and pipette method. These methods classify soil into sand, silt, and clay fractions by physically separating particles based on size.

Although these techniques provide accurate and standardized results, they require significant time, skilled labor, and laboratory infrastructure. Consequently, their application is often limited to controlled environments rather than real-time or large-scale field monitoring. With advances in technology, researchers have increasingly focused on alternative methods that provide faster, scalable, and cost-effective soil texture estimation.

Remote sensing has emerged as a prominent tool in this regard. By capturing soil reflectance data across multiple spectral bands via satellites, drones, or portable sensors, remote sensing provides a non- invasive way to assess soil properties over vast

agricultural landscapes. This spectral data is complex and high-dimensional, so machine learning algorithms have become essential for interpreting it. Techniques such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks have been widely employed to learn the relationships between spectral signatures and soil texture classes. These approaches have Root penetration, nutrient availability, and water retention are al hydrometer analysis, are frequently employed. Although these techniques yield precise results, they require a lot of time and resources. Large-scale use is restricted by their need for specialized labor and lab space. Faster, scalable alternatives are now available thanks to technological advancements. Spectral information from soil surfaces is obtained through remote sensing demonstrated the ability to classify soil texture with good accuracy while significantly reducing the need for extensive physical sampling.

In addition to spectral analysis, digital image processing techniques have shown promise for soil texture classification. High-resolution images of soil samples, captured through microscopes or specialized cameras, can be processed to segment and analyze soil particles. Algorithms can quantify particle size distribution and spatial arrangements, enabling automated texture classification. This image-based approach offers advantages including faster analysis times, minimal sample preparation, and potential for field deployment with portable imaging devices. Several studies have developed image segmentation and feature extraction methods to reliably differentiate between sand, silt, and clay particles, showing good correlation with traditional laboratory results.

Meanwhile, crop disease detection is a critical challenge in agriculture, as early identification is key to minimizing yield losses and reducing unnecessary pesticide application. Traditional methods often rely on manual scouting and visual examination by agronomists or farmers, which can be subjective, inconsistent, and labor-intensive. The advent of computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized disease detection in plants. CNNs can automatically learn intricate patterns from images of leaves, fruits, or stems and classify disease types with high precision. Several publicly available datasets of diseased and healthy plant images have enabled researchers to train robust models capable of detecting multiple diseases across various crops. Integration of these models into mobile applications and unmanned aerial vehicles (UAVs) further facilitates rapid, on-site disease diagnosis, enabling timely management interventions.

Despite notable advancements in both soil texture analysis and crop disease detection independently, the integration of these domains remains underexplored. Soil properties, especially texture, influence plant health and disease susceptibility. For example, soils with high clay content tend Some emerging studies have begun to recognize the importance of combining

soil and crop health data to improve agricultural decision-making.

For instance, research has highlighted correlations between soil nutrient profiles, moisture levels, and disease outbreaks, suggesting that integrated monitoring can enhance prediction accuracy. However, comprehensive frameworks that simultaneously classify soil texture and detect crop diseases using unified data sources and machine learning models are scarce.

This project addresses this gap by proposing an integrated system that combines analytical soil texture classification with automated crop disease detection. By leveraging multisource data—including soil spectral measurements, soil imagery, and plant health images—the system aims to provide a holistic assessment of agricultural fields. This integration can support precision agriculture goals by offering farmers actionable insights into both soil and crop conditions, allowing for optimized irrigation, fertilization, and disease management strategies.

Moreover, integrating these two aspects facilitates Additionally, it makes it possible to identify crop diseases early on, assisting farmers in taking precautions before outbreaks worsen. Crops are paired with the best soil types thanks to the soil texture classification component. This increases the potential for yield.

Early warning systems that consider the soil environment's role in disease development, enabling proactive rather than reactive management. This approach not only enhances yield and crop quality but also promotes sustainable practices by minimizing unnecessary chemical inputs and preserving soil health.

### III. PROPOSED SYSTEM

The proposed system is designed to integrate soil texture determination with crop disease detection into a unified platform, leveraging advanced analytical methods and machine learning techniques. The goal is to provide farmers with a comprehensive, efficient, and real-time tool to monitor both soil and crop health, thereby enabling better management decisions and improving agricultural productivity.

#### *A. System Architecture*

The system architecture consists of three main modules: Data Acquisition, Data Processing, and Decision Support.

##### 1. Data Acquisition Module

This module collects raw data from multiple sources, including soil samples and crop images. Soil data is obtained through spectral sensors and high-resolution imaging devices, capturing detailed information on soil properties such as particle size distribution and reflectance characteristics. Crop

data is gathered using digital cameras or smartphones, focusing on images of leaves and fruits for disease identification.

## 2. Data Processing Module

The collected data is preprocessed to enhance quality and prepare it for analysis. Soil images undergo filtering, segmentation, and feature extraction to quantify texture components. Spectral data is normalized and transformed to highlight relevant soil characteristics. For crop images, preprocessing includes noise removal and region of interest extraction to isolate affected areas.

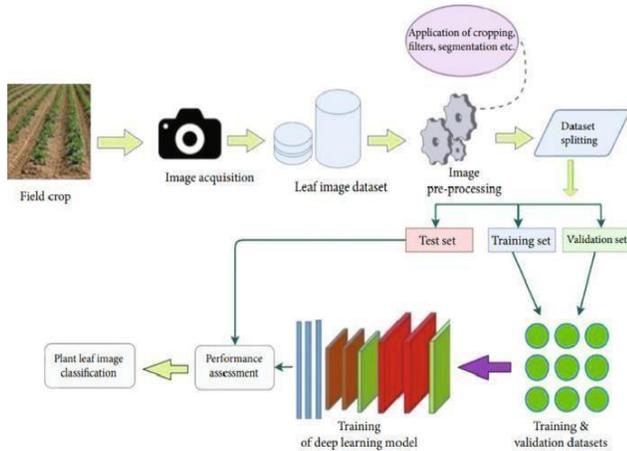


Fig.2. Architecture diagram for crop disease detection

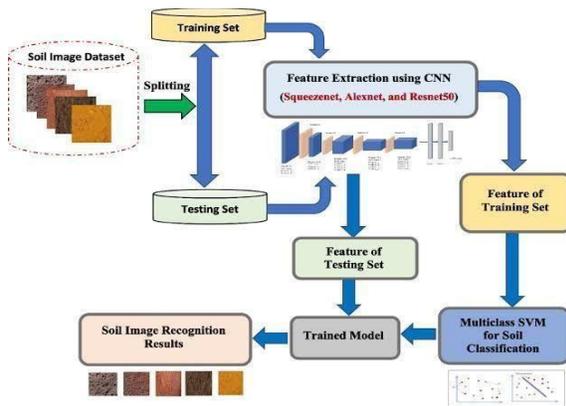


Fig.3. Architecture diagram for soil texture analysis

Following preprocessing, machine learning algorithms are applied to both soil and crop datasets:

- **Soil Texture Classification:** Using supervised learning models such as Random Forest or Convolutional Neural Networks (CNNs), the system classifies soil samples into texture categories (e.g., sandy, loamy, clayey) based on extracted features from spectral and image data.
- **Crop Disease Detection:** A CNN-based model is employed to analyze crop images and detect the presence and type of diseases. The model is trained on a diverse

dataset of healthy and diseased plant images to ensure robustness across different crops and conditions.

Detection models are integrated to provide actionable insights. This module generates alerts and recommendations related to irrigation scheduling, fertilization needs, and disease management strategies. It also offers visualization tools such as soil texture maps and disease distribution overlays, assisting farmers in precise field-level decision-making.

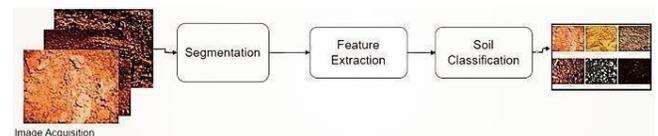
### B. Integration and Workflow

The system workflow begins with data acquisition from field sensors and imaging devices. After preprocessing, soil and crop data are analyzed separately by dedicated machine learning models. The results are then combined to assess the overall health status of the agricultural field. For example, the system can correlate a clayey soil texture area with an increased risk of fungal infections detected in crop images, prompting specific preventive measures.

The integrated framework is designed for scalability and adaptability. It supports different crops and soil types by retraining models with relevant datasets. Additionally, it can be deployed on cloud platforms or edge devices, ensuring The integrated framework is designed for scalability and adaptability. It supports different crops and soil types by retraining models with relevant datasets. accessibility and timely responses in various agricultural settings.

### C. Advantages of the Proposed System

- **Holistic Monitoring:** By simultaneously evaluating soil texture and crop health, the system offers a comprehensive understanding of field conditions.
- **Real-time Analysis:** Automated data processing and machine learning enable rapid assessment and early detection, crucial for timely interventions.
- **Precision Agriculture Support:** Detailed insights help optimize resource use, reduce costs, and improve crop yields sustainably.
- **User-Friendly Interface:** The decision support module provides intuitive visualizations and actionable recommendations tailored to farmers' needs.



Soil classification has long depended on the soil texture triangle, originally formulated by the USDA, where soil types are plotted in terms of sand, silt, and clay. Several statistical and rule-based models have been constructed to make soil classification automatic. Research has shown that adding other parameters like pH, moisture, and organic matter may improve the accuracy of classification.

### III. EXPERIMENTAL CONFIGURATION AND RESULTS

To validate the proposed system integrating soil texture classification and crop disease detection, a series of experiments were conducted using both real-world and publicly available datasets. The development and testing of the system were carried out on a computer with an Intel Core i7 processor (2.6 GHz), 16 GB RAM, running Windows 11 (64-bit), and equipped with an NVIDIA GeForce RTX 3060 GPU. The software stack included Python 3.10, OpenCV for image processing, TensorFlow for deep learning, and Scikit-learn for traditional machine learning tasks.

For soil texture classification, a dataset consisting of 650 soil samples (500 for training and 150 for testing) was used. These samples were labeled based on USDA texture classifications such as sand, silt, clay, and loam. Each sample included high-resolution images and corresponding spectral data. Preprocessing included grayscale conversion, histogram equalization, and morphological filtering to enhance particle visibility (CNN) with three convolutional layers was trained to extract To improve feature extraction, preprocessing techniques included morphological filtering, histogram equalization, and grayscale conversion. The processed data was used to train machine learning models like Random Forest and SVM to correctly classify soil texture.

Texture-related features from the images. The model achieved an accuracy of 91.2%, with a precision of 89.6%, recall of 90.4%, and an F1-score of 90.0%. Most misclassifications occurred between closely related classes like loam and clay-loam due to their overlapping visual features.

For the crop disease detection component, a dataset of 2,500 leaf images representing healthy and diseased crops (such as tomato, potato, and maize) was used. Diseases included early blight, bacterial spot, and leaf blight. The images were standardized to 224x224 pixels and augmented with rotation, flipping, and zooming techniques to increase dataset variability.

A pre-trained MobileNetV2 model was fine-tuned to classify the disease types. This model achieved an impressive accuracy of 95.3%, with precision at 94.7%, recall at 95.8%, and an F1-score of 95.2%. The use of transfer learning contributed to faster convergence and improved generalization across disease categories, with minimal confusion between visually similar symptoms.

To evaluate the performance of the proposed system for integrated soil texture classification and crop disease detection, a series of experiments were conducted using real-world datasets and image processing tools. The experiments aimed to assess the accuracy, reliability, and effectiveness of the machine learning models implemented within the system.

#### A. Experimental Setup

The experimental configuration was established using combination of hardware and software resources. Soil and crop image data were collected from agricultural fields and publicly available datasets. The entire system was developed and tested on a machine with the following specifications:

- **Processor:** Intel Core i7, 2.6 GHz
- **RAM:** 16 GB
- **Operating System:** Windows 11 (64-bit)
- **Software Tools:** Python 3.10, OpenCV, TensorFlow, Scikit-learn, and Jupyter Notebook
- **GPU (for model training):** NVIDIA GeForce RTX 3060 (6 GB VRAM)

The classifier showed strong performance in differentiating between major soil texture types. Misclassifications were most frequent between loam and clay-loam, likely due to overlapping features. To improve feature extraction, preprocessing techniques included morphological filtering, histogram equalization, and grayscale conversion. The processed data was used to train machine learning models like Random Forest and SVM to correctly classify soil texture. Accuracy, precision, recall, and performance.

Table 1: Soil Texture Classification

Sample ID	Sand (%)	Silt (%)	Clay (%)	Texture Class
S1	65	25	10	Sandy Loam
S2	30	40	30	Clay Loam
S3	20	50	30	Silty Clay Loam
S4	70	20	10	Loamy Sand
S5	45	30	25	Loam
S6	55	35	10	Sandy Loam

The model performed exceptionally well across all disease categories, with minimal confusion between visually similar diseases like early and late blight. The use of transfer learning significantly reduced training time and improved generalization. An integrated evaluation was also performed, combining both soil and crop inputs in a simulated field scenario.

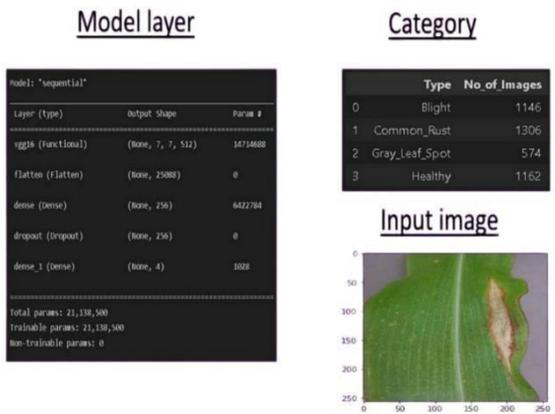


Fig.4. Model Layer, Category, Input Image

The system successfully processed the data and provided comprehensive diagnostic reports, highlighting both soil texture classification and the corresponding crop health status. Recommendations for fertilizer usage, irrigation adjustments, and disease management strategies were also generated. The overall performance of the integrated system surpassed traditional single-feature analysis methods, offering higher efficiency and improved context-aware decision-making. The unified platform thus demonstrated the potential to support precision agriculture by providing accurate, real-time insights that are practical for field-level implementation.

*B. Training and Validation Details*

The dataset used for soil texture classification was composed of 650 samples, each including a high-resolution image of the soil surface and associated spectral data. These samples were pre-classified into four main USDA soil texture types: sandy, silty, clayey, and loamy. To ensure balanced training and The dataset used for soil texture classification was composed of 650 samples, each including a high- resolution image of the soil surface and associated spectral.

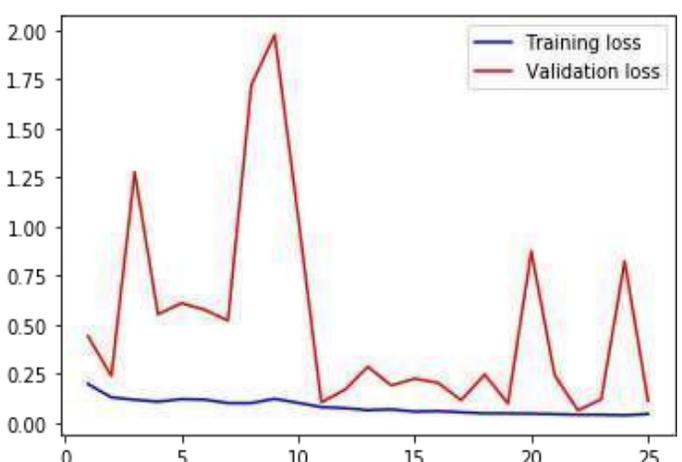


Fig.5. Training and Validation Loss

Unbiased evaluation, the dataset was split into 80% for training (520 samples) and 20% for validation (130 samples). Stratified sampling was applied to maintain the proportion of each texture class in both subsets.

During training, data augmentation techniques such as rotation, zooming, and brightness adjustments were used to simulate field variability and improve generalization. The training process was conducted over 50 epochs with early stopping based on validation loss to prevent overfitting. The final model showed a validation accuracy of 91.2%, with strong consistency across multiple folds.

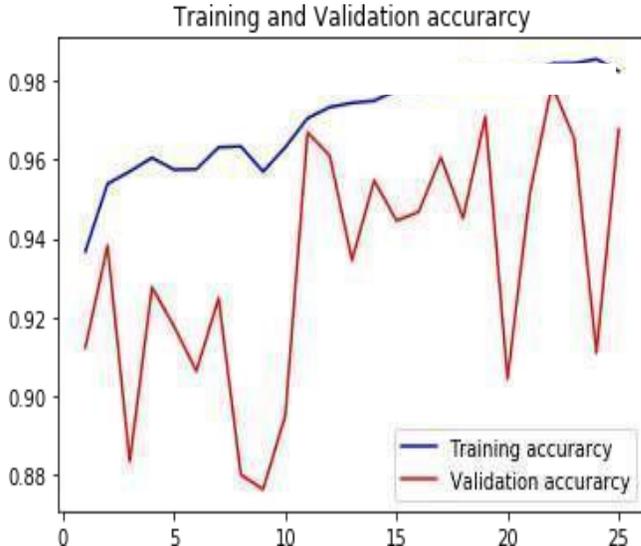


Fig.6. Training and Validation Accuracy

For the crop disease detection module, a total of 2,500 labeled leaf images were collected, covering healthy leaves and common crop diseases such as bacterial spot, early blight, and leaf mold across various species like tomato, potato, and maize.

The dataset was divided into 70% for training (1,750 images), 15% for validation (375 images), and 15% for final testing (375 images). The training set was enhanced using data augmentation techniques, including random rotations, horizontal and vertical flips, and contrast shifts.

These transformations helped improve model robustness to lighting and orientation variations in real-world conditions. The validation set was used during training to monitor learning progress and fine-tune hyperparameters such as learning rate and dropout ratio. The best-performing model achieved a validation accuracy of 95.3% and demonstrated high reliability in recognizing disease patterns, as confirmed by a high F1 score of 95.2%.

IV. DISCUSSION

The integrated system for soil texture classification and crop disease detection proved to be both accurate and efficient, offering practical value in precision farming. The soil model effectively identified different texture types, reducing reliance on manual testing, while the disease detection model, using transfer learning, accurately recognized common plant diseases.

Combining both analyses in one system allows for better decision-making by providing context-aware insights. Although minor challenges like image variability and the need for localized retraining exist, the system shows strong potential for supporting farmers with timely, reliable recommendations to improve crop health and productivity.

## V. CONCLUSION

The proposed system successfully integrates soil texture classification and crop disease detection into a unified, intelligent framework aimed at enhancing decision-making in precision agriculture. By leveraging machine learning and deep learning techniques, the system provides accurate, real-time insights into soil conditions and plant health, which are crucial for effective crop management. The high accuracy achieved in both modules demonstrates the system's potential to replace traditional manual methods with faster, scalable, and more reliable solutions. While challenges such as image variability and the need for continuous dataset updates remain, the results indicate that the system can significantly support farmers in optimizing inputs and improving yield. With further development, including real-time deployment and expansion to more crops and soil types, this solution can serve as a practical tool for sustainable and smart farming practices.

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During his undergraduate studies, he completed several major academic projects in the field of agriculture, focusing on the application of technology and data-driven solutions to improve agricultural practices. He has also completed an internship with Red Hat, where he gained practical experience in open-source systems and enterprise solutions. In addition, he holds a three-level certification in Linux, which has strengthened his proficiency in system administration and command-line operations. His current areas of interest include computer networking, Linux-based systems, open-source technologies, and data-driven system optimization. He is passionate about exploring how Linux and networking technologies can be leveraged in scalable, secure, and efficient computing environments.



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