Deep Learning-Based Determination of Cocopeat for Water Retention in Agricultural Practice

PROJECT PHASE I REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Soil surface texture classification using RGB images represents an innovative approach to soil analysis, providing a cost-effective and efficient alternative to traditional methods. This study explores the potential of using RGB imagery, captured by standard digital cameras, for accurate classification of soil textures, including cocopeat. By applying image processing techniques and machine learning algorithms, we aim to distinguish between different soil textures such as sand, silt, clay, and cocopeat. The methodology involves collecting soil samples, including cocopeat, capturing high-resolution RGB images, and pre-processing these images to enhance feature extraction. Key features, including color histograms, texture descriptors, and spatial patterns, are extracted and used to train classifiers such as Support Vector Machines (SVM),Random Forests, and Convolutional Neural Networks (CNN). Preliminary results demonstrate that RGB imagery can effectively capture significant textural differences, including those of cocopeat, enabling accurate classification with high confidence levels. This approach offers significant advantages, including rapid data acquisition, non-destructive sampling, and the potential for large-scale application through drone and satellite imaging. Future work will focus on refining the algorithms for better accuracy, expanding the dataset to include more variations of cocopeat, and integrating this technology into real-time soil monitoring systems.

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SVM -Support vector machine

RF -Random forest

CNN - nvolutional neural network

GLCM - Gr y level co-occurrence matrix

RGB - Rc green blue

LDA - Linear discriminant analysis

KNN - K nearest neighbour

CHAPTER 1

1. INTRODUCTION

1.1. GENERAL

With the increasing global population, the scarcity of water resources will be intensified to make this issue one of utmost importance in managing water in agriculture. Saving water is very important in agricultural productivity and also in the long run survival of farming. Cocopeat, as a product of processed coconuts, has now become an important substrate in agriculture since it can retain water to create a suitable environment for plants to grow steadily. The only challenge is in determining how much coco pith is suitable for what type of soils as they pose different water-holding capacities and environmental requirements. The traditional ways of substrate management are mostly based on heuristic methods or general guidelines that do not consider the diversities found in plant species as well as the environment.

Soil texture classification is an integral part of soil science, with a critical impact on nutrient availability, water retention capabilities, and crop production. Despite their reliability, such approaches as sieving and sedimentation test are time-consuming, laborious, and require special knowledge and equipment, thereby limiting their scale. Integration of advanced technologies such as machine learning and image processing provides novel solutions to this set of problems. The paper shows a scalable, non-invasive system intended for soil texture analysis from RGB-photos taken with standard digital cameras. Such RGB photos contain rich details about the color and texture of soil and its spatial patterns. So, computation analysis of these characteristics makes possible the accurate classification of soil types. The system includes Cocopeat recommendations, which relate soil texture characteristics to the required quantity of Cocopeat for improving soil quality. This project therefore offers a tool that may practically help in the optimization of soil management practices for farmers, researchers, and environmentalists.

For assessing soil texture in order to enhance the agricultural techniques, water management, and environmental sustainability, it is essential to classify the texture properly. The existing methods like hydrometer testing and sieve analysis are time consuming, costly, and inappropriate for real-time or high-volume use. Since they require controlled laboratory settings, they cannot be accessed for on-site or field-level analysis. Moreover, the soil has regional heterogeneity hence a more flexible and scalable strategy is required. A potentially usable alternative is RGB image-based soil analysis, whereby digital cameras, or rather any other widely available camera, will capture and classify soil textures based on structural as well as visual features. However, there are some barriers to overcome, such as lighting changes, climatic conditions, and the inherent complexity of the appearance of the soil. The paper addresses these challenges by constructing a robust framework for the automated classification of soil texture using techniques of image processing and machine learning. Besides that, it integrates Cocopeat recommendations, which provide guidelines on amending the quality of soil based upon the texture, hence offering a more holistic approach to the management of soil.

1.2. OBJECTIVE

1.2.1. Soil Texture Classification:

The goals are to classify various soil textures like sand, silt, clay, and cocopeat using RGB photographs in a reliable manner. This technology offers the quicker and better inexpensive method to manage agriculture as well as the environment by making use of machine learning algorithms processing visual data rather than the labor-intensive traditional approach.

1.2.2. Feature Identification And Extraction:

The targeted information extracted from RGB images by the research comprises spatial patterns, texture descriptors, and color histograms. These features help the machine learning models provide the machine learning model with crucial information that relatesto the physical and visual characteristics of soil, thereby helping in distinguishing different types of soils with exact classification.

1.2.3. Coco Peat Recommendation:

Based on its texture and qualities, this purpose is looking forward to suggesting the ideal amount of cocopeat required for enhancing soil health. The device helps users improve water retention and nutrient absorption by evaluating soil properties-including moisture content and porosity-guaranteeing sustainable and effective cocopeat use.

1.2.4. Real Time Analysis:

This system will develop an intuitive interface for classifying soil textures in real time and recommending cocopeat. This mobile or drone-based application is to allow users to analyze soil in the field, making its results instantaneous. This will achieve extensive monitoring of soil and effective agricultural decision making.

1.2.5. Enhanced agricultural decision making:

Technology allows for an accurate determination of soil characteristics and provides an optimum amount of cocopeat that may enhance soil aeration, water retention capacity, and fertility. Consequently, decisions on fertilizers, irrigation, and crops are performed more readily, and this culminates into increased output and sustainable practices of farming.

1.3. EXISTING SYSTEM

One of the traditional methods of classifying soil texture has been through sieving or hydrometer tests, which had been used for a long time in the analysis of soils. These techniques are rather accurate but time-consuming, tiresome, and require special equipment and expertise. For example, sieving separates soil into size fractions. In the hydrometer method, sedimentation rates determine the percentages of sand, silt, and clay. Such methods are very challenging to scale to large area or real-time analysis due to their logistics demands and dependence on laboratory settings.

These conventional methods also have inaccessibility problems, especially for areas far-flung or with low resources where laboratory stations and experts might be scarce. Furthermore, the time consumed by sample collection, transport, and processing might prevent quick decisions that are sometimes needed at planting time or during changes in the environment. Moreover, human techniques involve variability and subjectivity which depend on the technician used and different interpretations of the method.

Emerging technologies hold promise for these applications. Remote sensing offers a wide field view, yet it is often less accurate for focussed detailed analysis. More promising promises that digital imaging and machine learning hold. RGB images captured at such high resolution from standard cameras can be analyzed for features like color histograms and texture patterns to classify soil texture with machine learning models.

Soil texture analysis has been automated with rapid and accurate classifications by using machine learning algorithms, such as SVM, RF, and CNN. These models are trained on labeled datasets and generalized well to new soil samples. Significant challenges persist in collecting diverse datasets that can address the regional and environmental variability, as well as in dealing with the imaging conditions, like lighting and moisture of the soil, which affect the accuracy of the classification.

These advanced techniques should be turned into useful tools with friendly user interfaces, such as mobile applications, which would be intuitive and accessibly deployed on common devices, supported by training programs for end-users like farmers and land managers. Such technological innovations provide efficient, scalable alternatives to traditional methods, but their success depends on overcoming challenges in data, model development, and user adoption.

1.4. PROPOSED SYSTEM

The proposed framework for soil texture classification using RGB imagery and machine learning would negate the conventional, laborious approaches to soil assessment, which depend on sieving and sedimentation analysis. Such approaches are notorious for their time requirements and specialized equipment and expertise. In contrast, the proposed system utilizes high-resolution RGB images that can be gathered with standard digital cameras, making the process more accessible and less expensive in general. This system makes it easier to collect the data and, therefore can be used with field applications or in an extensive monitoring process. The system focuses on characteristics of the soil surface such as color, texture, and spatial arrangements, for easy, non-invasive, and instantaneous analysis.

The procedure commences with the acquisition of soil samples from diverse sites and depths, thereby guaranteeing a representative dataset. The soil is processed within a regulated environment characterized by uniform lighting to obtain high-quality images. Following the capture of the images, they are subjected to pre-processing techniques such as noise reduction and contrast enhancement to promote consistency and enhance the precision of the analysis. Subsequently, the pre-processed images are examined to identify critical features that reflect the texture of the soil.

The key characteristics, such as color histograms, texture descriptors of the kind - that of Local Binary Patterns or Gray Level Co-occurrence Matrix - and spatial patterns, are extracted from the images. Characteristics, so extracted, are the backbone for the identification of different soil textures, like sand, silt, clay, etc. Machine learning algorithms, including Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN), are learned on this labeled dataset which contains all these features. These models are aimed at establishing relationships between different visual features and various soil types, thus enabling the system to categorize novel, unseen soil samples correctly.

At the end of the training process, the system will classify soil texture in an instant, through a user-friendly interface, be it an application for mobile or a web-based platform. Users can either upload photographs of their soil sample or capture through their devices. The system then analyzes the image; classifies the soil texture, and comes up with results in real time. This feature is very convenient because one can make quick decisions regarding soil types, hence the managerial inputs about the land.

The system further includes a Cocopeat Recommendation Module that provides personalized tips for users to improve the quality of their soil. After determining the proportionate measurement of the categorized soil texture (sandy, clayey, or silty), the system provides the best amount of cocopeat needed. This allows the system to change appropriately under different classes of soils and conditions by continually refining its models with further input data, which serves to continuously improve the accuracy over time.

In addition, it has been designed to be adaptive, thus best suited for application in a wide variety of agricultural, environmental, and research applications. By aligning with the principles of precision agriculture, it is necessary to provide support to farmers to make the right decisions in terms of irrigation, fertilization, and crop selection that may considerably improve crop yields while being resource-friendly. Implementation of this technology into the existing agricultural management system is currently underway. Subsequently, users will now have an integrated interface because digital tools are becoming an integral part of agricultural methodologies. This allows the system to effectively adapt to different soil types and conditions under a continuous evolution of its models as new data is acquired for the development of better accuracy over time.

It has also been designed with flexibility, thus suitable for implementation across a wide range of agricultural, environmental, and research contexts. It would be in line with the precision agriculture philosophy to help farmers decide on matters of irrigation, fertilization, and crop choice, which are probably more likely to benefit crops yields while optimizing the use of resources. This technology is being implemented into the current management systems for agriculture. As such, users will be presented with a seamless experience as digital tools come to be included in agricultural practices.

In conclusion, the proposed soil-texture classification system marks a modern and efficient system that puts together digital imaging and machine learning for accurate and real-time soil analysis. This system offers an intuitively geared framework that enables the agricultural producers, researchers, and environmental administrators to make timely, knowledge-based decisions while optimizing their strategies on the management of the soil. It can, therefore make the process of conducting a soil analysis even easier, cost-effective, and practical compared to other traditional methods, thereby encouraging good stewardship of the environment and sustainable agricultural practices.

CHAPTER 2

2.1.LITERATURE SURVEY

The literature survey depicts progress in soil texture and fertility classification using machine learning (ML) and deep learning (DL) methods. These include studies that use different algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs) and hybrid models, thereby exhibiting innovation in terms of feature extraction, improvement in accuracy of classification, and application in practical usage. While one research focuses on classification of soil texture and nutrient, another merges these classification methods with applications such as crop recommendation and Cocopeat usage.

The studies show a lot of progress in terms of accuracy and scalability but identify problems like variability of datasets, computational complexity, and real-world implementation constraints at the same time.Multi-Feature Fusion for Soil Image Feature Extraction and Classification Using Machine Learning by Kiran Pandiri et al. [1] a multiple-feature fusion method applied to the classification of soil texture is shown. Classification purposes are served by the method applying Gaussian-kernel SVM, using a combination of GLCM, Tamura descriptors, Gabor filters, and HSV texture features.

The multi-feature method enhances robustness in classification because it draws upon multiple dimensions of soil texture. While the methodology is innovative, the study lacks detailed performance metrics and comparisons with other classification techniques, leaving its practical impact unclear. Soil Classification using Deep Learning Techniques by Sivabalaselvamani et al. [2] discuss the use of CNNs, particularly VGG19 architecture, to evaluate a 94.87% accuracy in soil texture classification.

The research addresses its potential applications in agriculture, geology, and engineering. Deep learning is applied to extract patterns of textures at a high precision level. However, the attention given to the dataset is minimum and even less to comparisons with other methodologies, so this cannot be properly evaluated for robustness and scalability.Optimized Hybrid Soil Texture Classification Model Based on Stacked Sparse Autoencoder by Prabavathi and Chelliah [3] suggest a hybrid approach combining DBSCAN for clustering and SSAE for classification; this achieves accuracy at 95.66%.

This kind of hybrid model makes the approach more capable in the complexities of soil texture patterns, thus promising to be an efficient tool for the classification of soil. Therefore, whereas this model does have very high accuracy, the model's complexity and computational demands are severe drawbacks, specially in real time or resource-constrained applications. Soil Classification, Crop Selection, and Prediction of Fertilizer Based on Soil Series by Varsha et al. [4] emphasis the applied use of ML in agriculture by predicting fertilizers based on the soil type and environmental factors.

Crop selection to acquire optimum yields is also assisted through the study. The methodology has been pragmatic, though the specifics about particular ML algorithms and performance metrics are missing, which restricts the understanding of its effectiveness. However, its focus on real-world agricultural problems underlines its importance.Cocopeat Classification of Soil Nutrient with the help of Deep Learning to Enhance the Precision by Rathore and Singh [5] used CNNs in combination with OpenCV and TensorFlow for the classification of soil nutrients along with Cocopeat.

Deep learning is powerful in boosting efficiency in agricultural production, and the paper applies precision fertilizer application. However, very limited information was presented about the dataset that was used and its characteristics and comparisons with other traditional methods that would have helped to provide much-needed context to real-world applications. Visual Transformer for Soil Classification by Jagetia et al. [6] presented Visual Transformer models for the soil classification task with an accuracy of 93.62%. This outperformed performances of SVM, AlexNet, ResNet, and CNN models. This work emphasizes the effectiveness of transformers for complex datasets used in soil image classification. While promising results are presented, the discussion on dataset variability and scalability is somewhat meager.

Machine Learning Based Classification of Soil Texture by Ghabi [7] ML methods are utilized in the soil texture classification process, in particular LDA and KNN. This approach pays attention to precision and reliability in conducting its classification accuracy.Yet, this contribution lacks detailed comparison of algorithms and dataset characteristics, which may be improved and is worth further study. Fusion of Enhancing Target Features and Focusing Slice Features for Soil Image Classification by Zheng et al. [8] presented a new three-branch network for feature enhancement and focusing, achieving results competitive with the current state-of-the-art for soil image classification.

A more advanced model architecture ensures fine-grained classification, which is very applicable on complex soil textures. Its complexity in implementation and scalability continue to be challenges when applied in real-time scenarios.CNN-Based Soil Fertility Classification with Fertilizer Prescription by S. M. and Jaidhar [9] achieve 97.52% accuracy using CNNs for soil fertility classification and fertilizer prescription. The study makes use of different sizes of kernel and input grid, thus improving the accuracy of the classification.

Though its accuracy is impressive, the study does not discuss dataset variation and real-world issues that would influence its practical implementation. Classification of Soil Fertility Level Based on Texture with Convolutional Neural Network (CNN) Algorithm by Natsir et al. [10] applied an optimization technique to CNN parameters for the classification of soil fertility level using texture with an accuracy of 94.24%. The classification performance as this technique focuses on CNN optimization makes it a valuable contribution towards the study of soil texture but explores limited robustness and scalability of the model, thus restricting its more extensive application.

CHAPTER 3

3. SYSTEM DESIGN

3.1. GENERAL

3.1.1. SYSTEM FLOW DIAGRAM

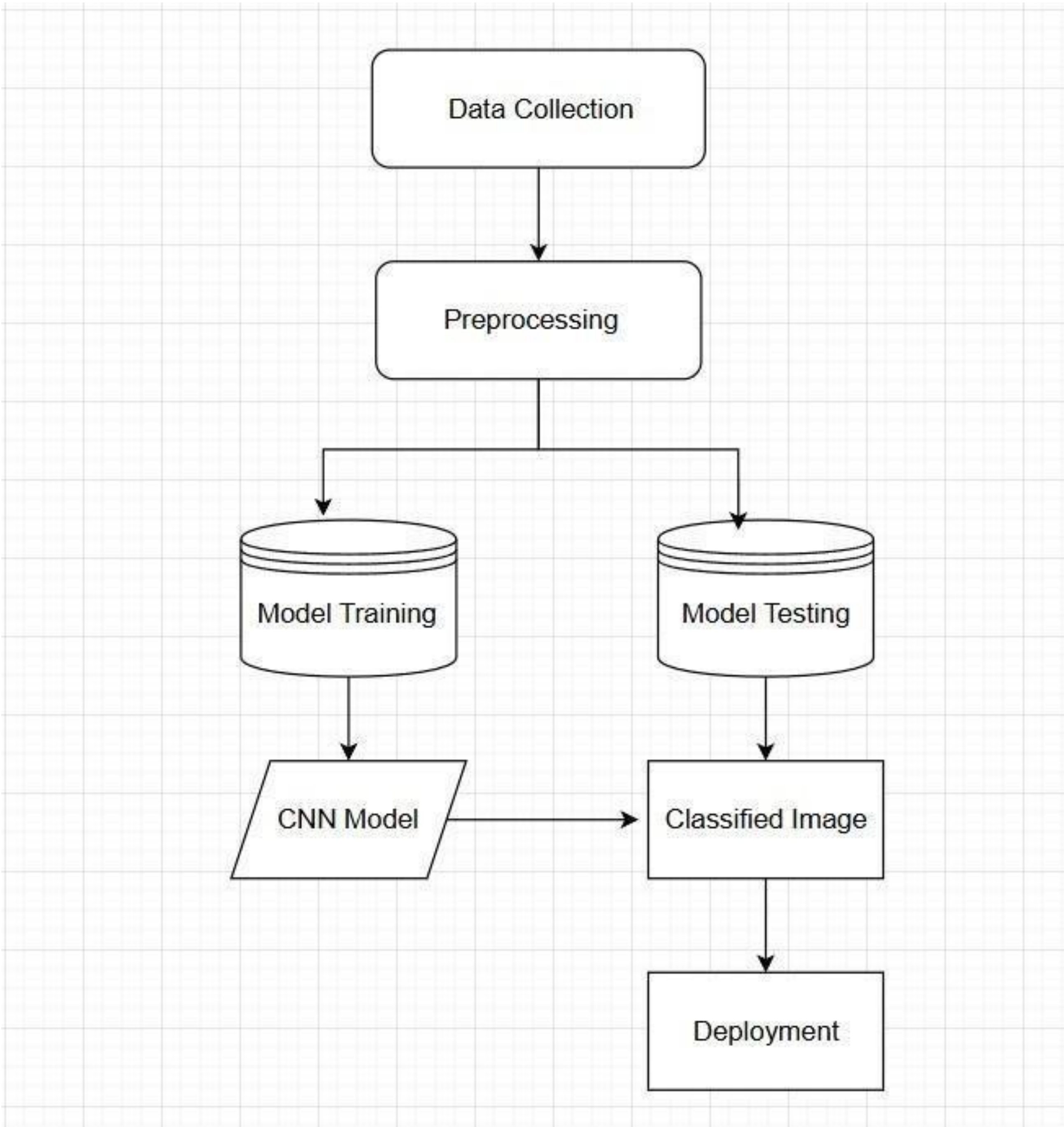

Figure 1 System Flow Diagram

3.1.2. SEQUENCE DIAGRAM

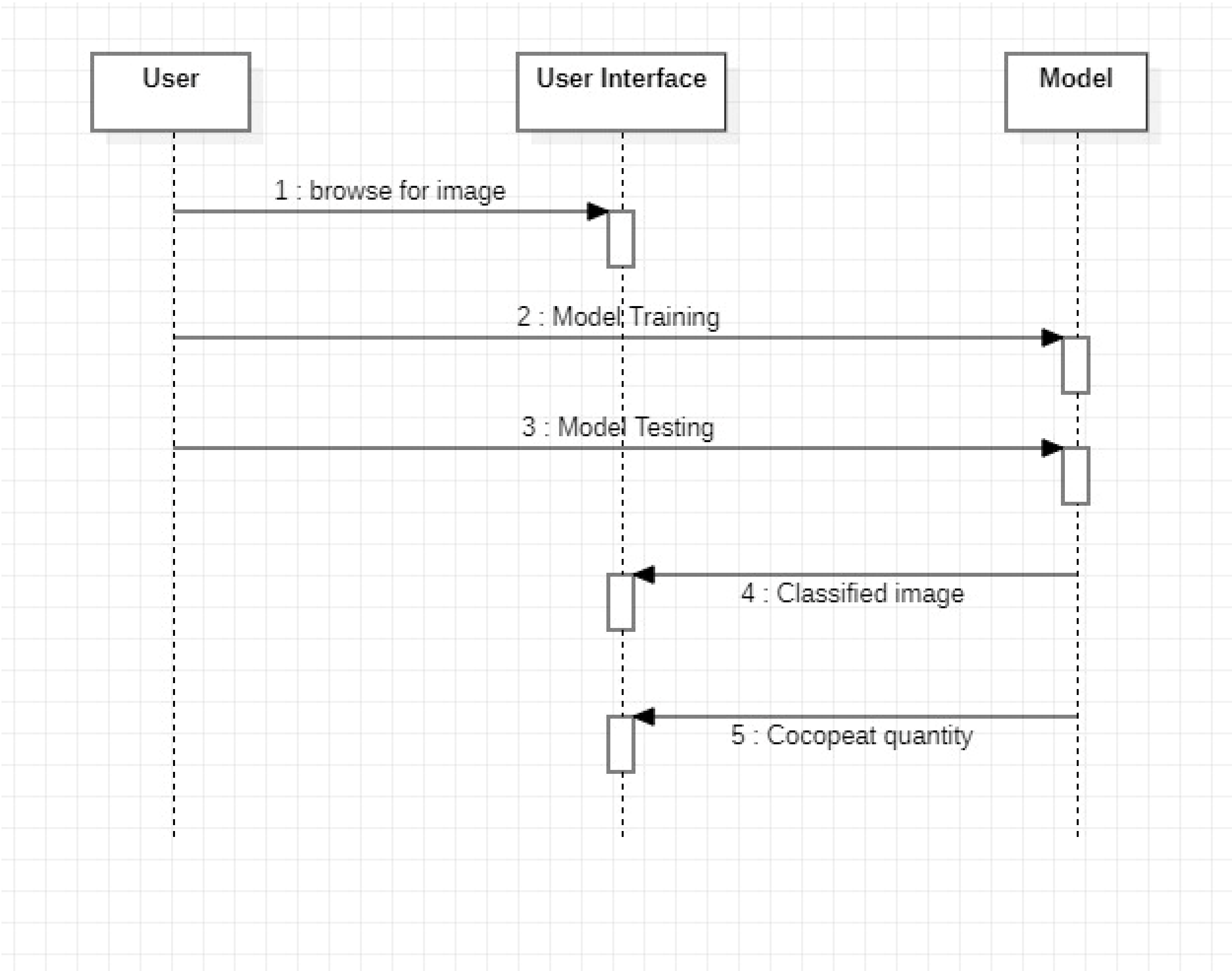

Figure 2 Sequence Diagram

3.1.3. CLASS DIAGRAM

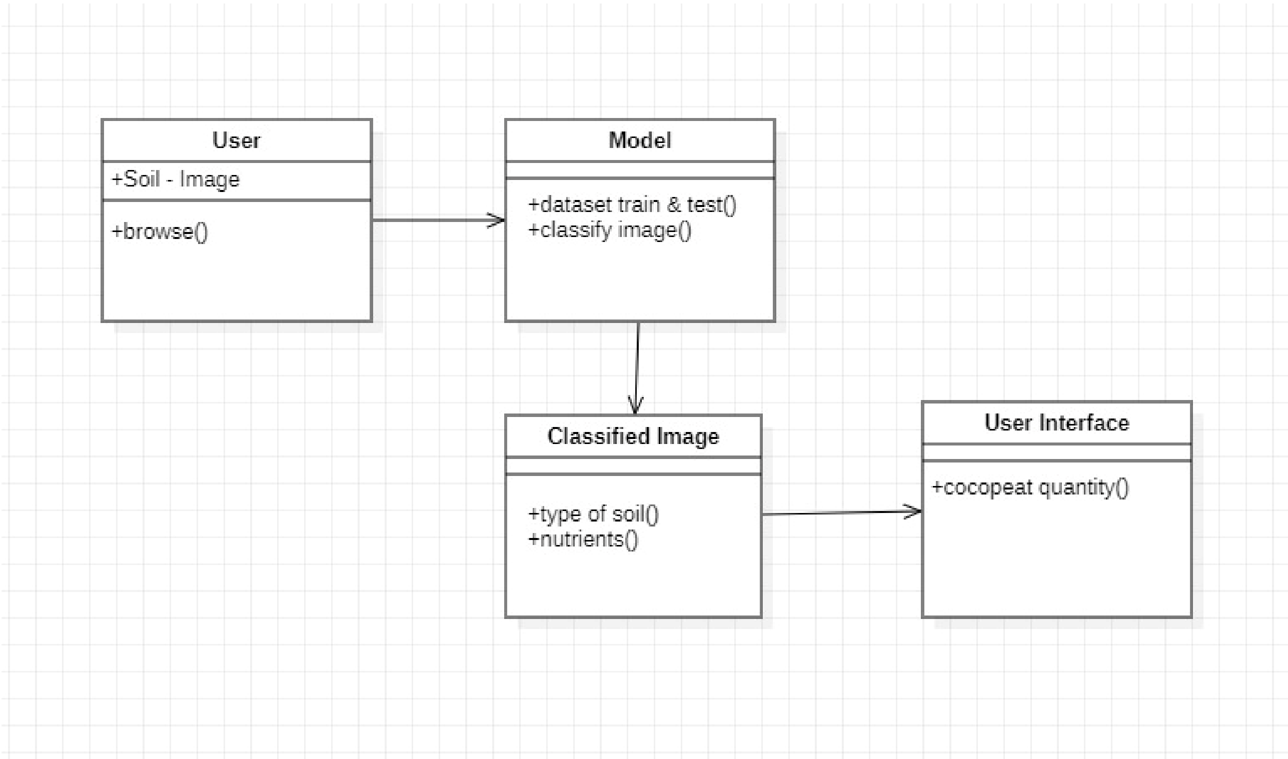

Figure 3 Class Diagram

3.1.4. USE CASE DIAGRAM

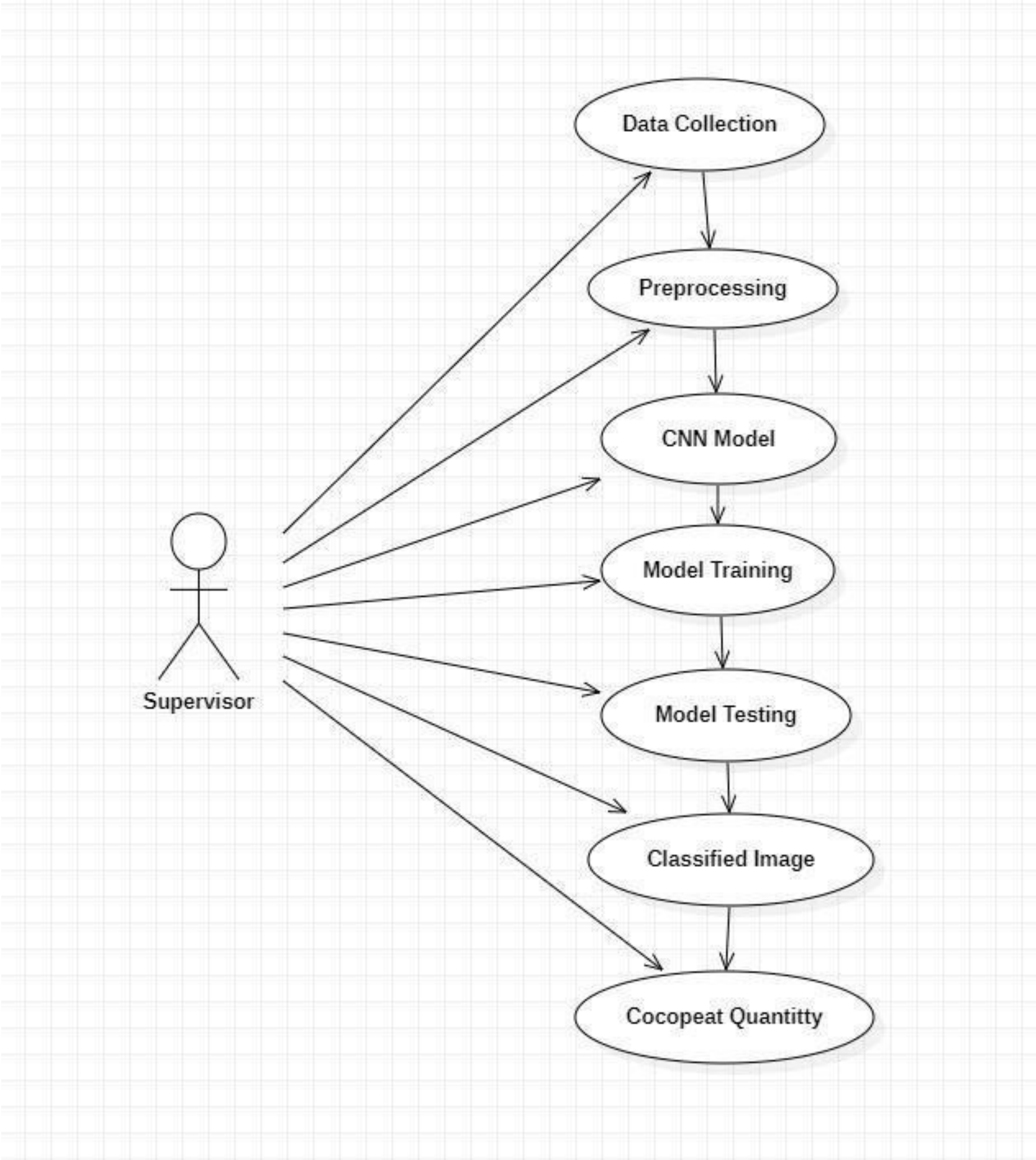

Figure 4 Use Case Diagram

3.1.5. ARCHIETECTURE DIAGRAM

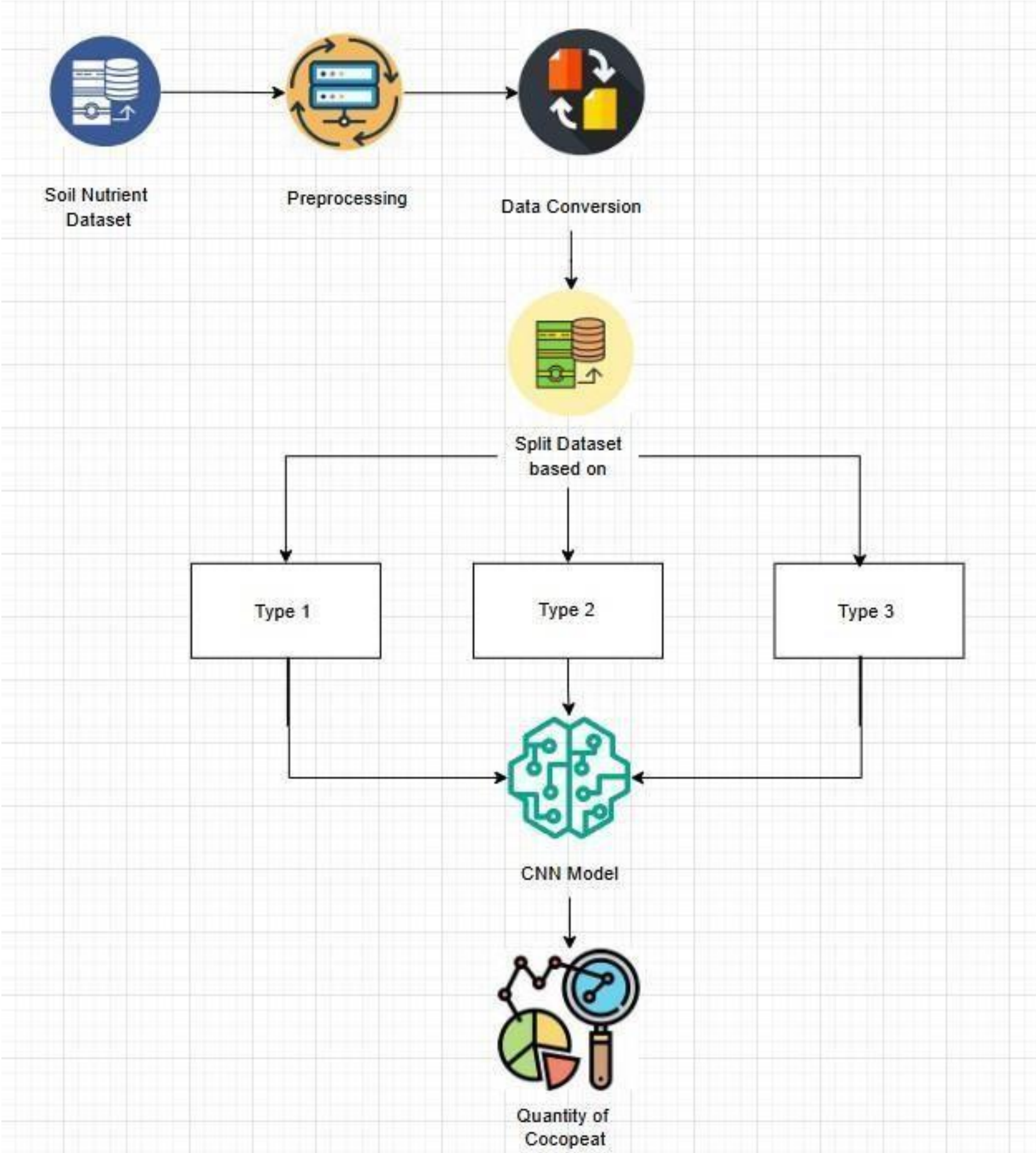

Figure 5 Architecture Diagram

3.1.6. ACTIVITY DIAGRAM

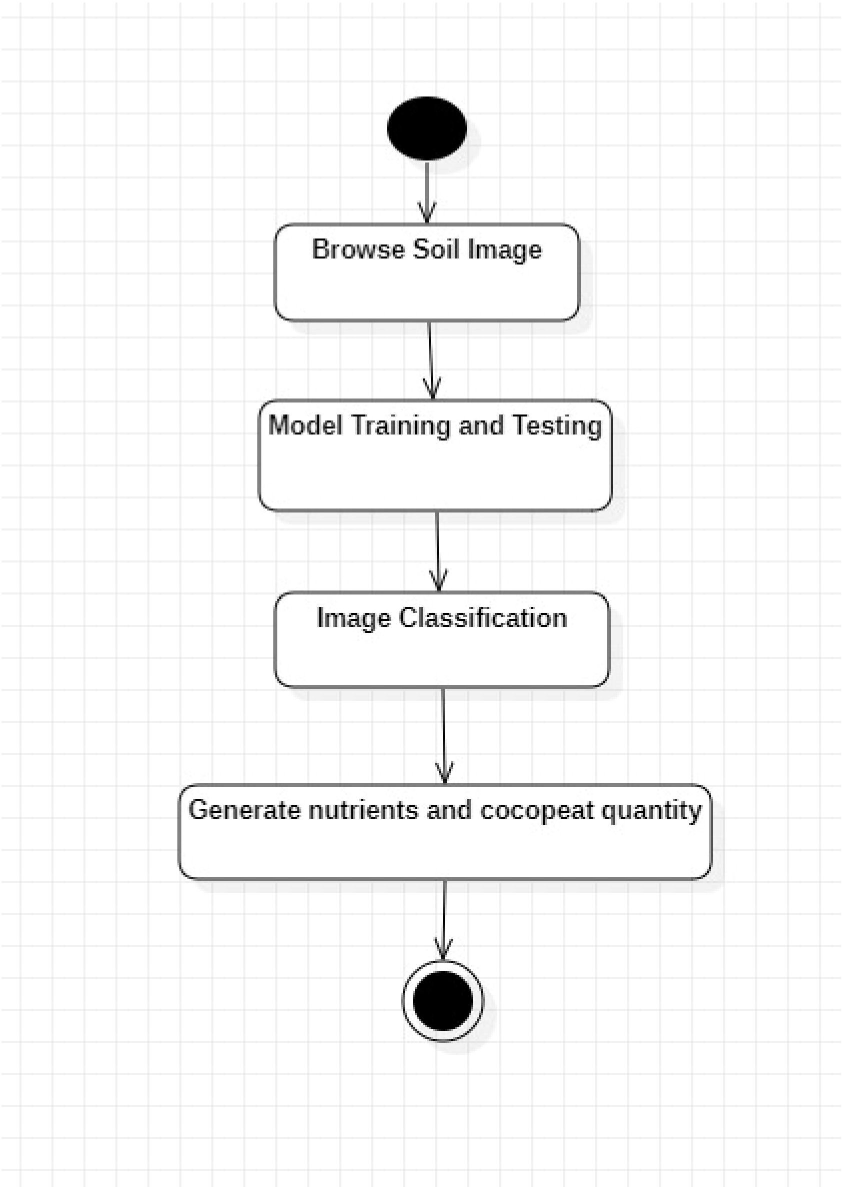

Figure 6 Activity Diagram

3.1.7. COMPONENT DIAGRAM

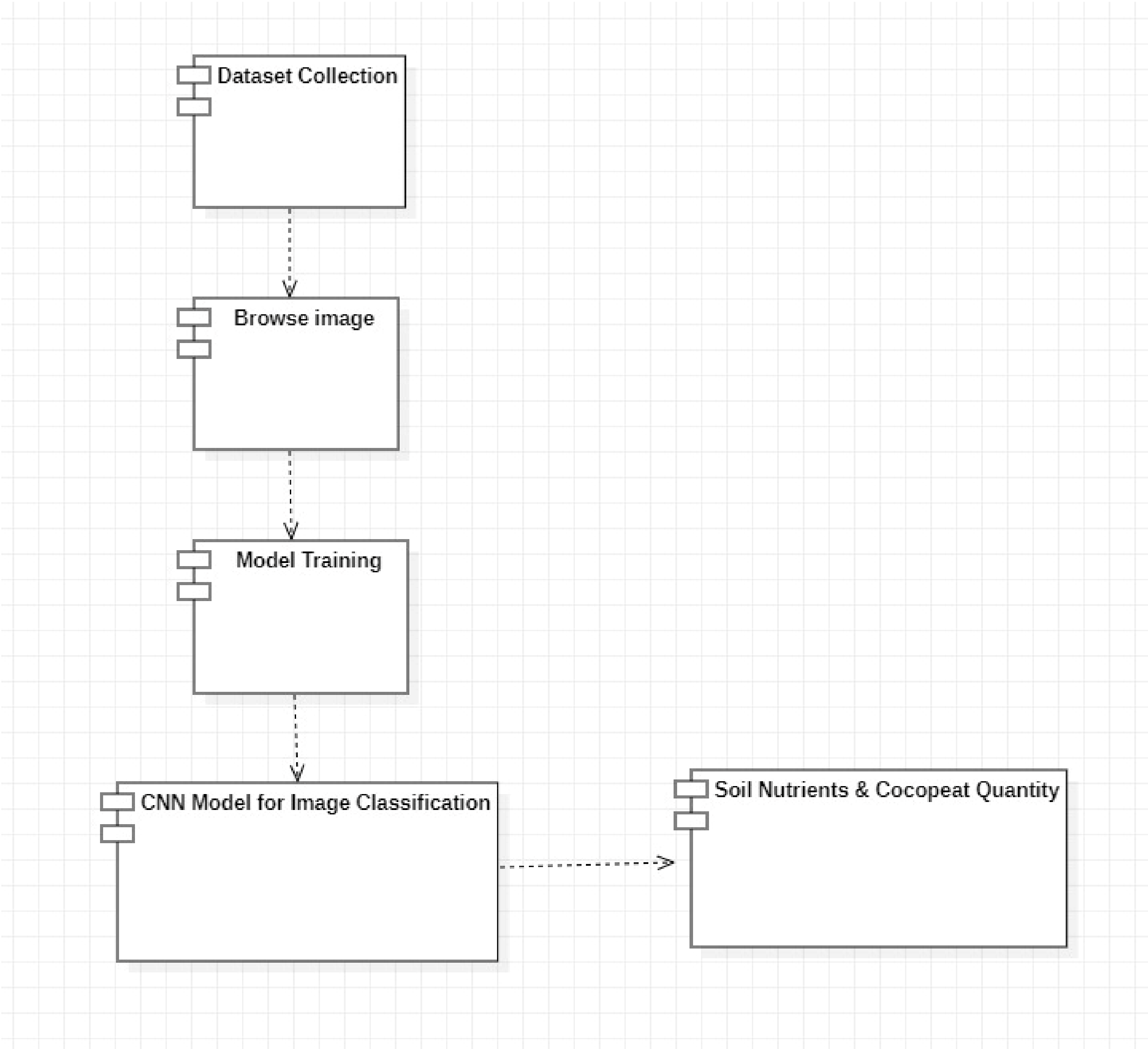

Figure 7 Component Diagram

3.1.8. COLLABORATION DIAGRAM

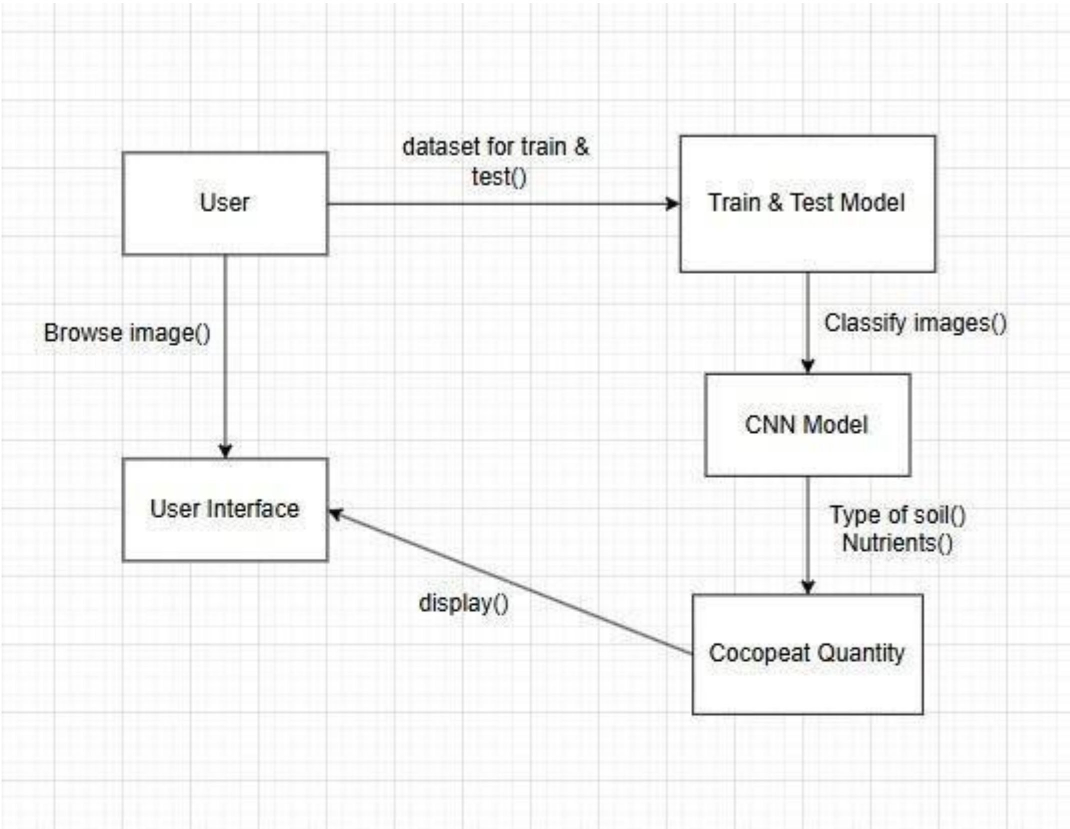

Figure 8 Collaboration Diagram

CHAPTER 4

4. PROJECT DESCRIPTION

4.1. METHODOLOGIES:

The soil texture classification project replaces the long process of traditional sifting and sedimentation with more expeditious machine learning and RGB pictures to speed up the analysis of soil. High-resolution photographs of soils are taken using standard cameras and preprocessed and inspected for information such as spatial patterns, texture descriptors, and color histograms. Many labeled datasets can be applied to trainthese models towards classifying the soil texture, which includes the type of sand, silt,and clay. Applying supervised learning techniques such as SVM, Random Forests, and CNN.There is the module on Cocopeat Recommendation in the system that offers useful tips on how one could improve soil quality based on its texture. For example, it computes how much cocopeat should be added to increase aeration in clayey soils or increase water retention in sandy soil. Furthermore, the module gives application guidelines in full recommendation to ensure maximum output for healthy soils that can be farmed well.

1. Data Collection And Preprocessing:

This preliminary stage of the project involves data collection and preprocessing, with an emphasis on getting a wide range of soil samples, including cocopeat, from various geographical locations and agricultural fields. These samples range in texture from sand to silt, clay, and mixes, in order to ensure that the model produced will be reliable and effective in generalizing over many soil types. This dataset considers cocopeat, a widely used soil modifier prized for its aeration and water holding capacities, as a different class. To reduce differences introduced by shadows or reflective surfaces, high-resolution RGB images of each soil sample are captured under strictly controlled illumination. These images are preprocessed: scaled in consistent resolution, histogram equalization is applied for contrast, filters are applied to reduce noise. For consistency within the dataset, the segmented images, which separate the soil surface from the background, are normalized before being used in feature extraction.

2. Feature Extraction:

During the feature extraction step, the important features that distinguish various soil textures are found and processed. Among these salient aspects are the color histograms showing the distribution of hues, which inform about moisture and content of organic matter. Texture descriptors, including the GLCM, Gabor filters, and Tamura analysis, are used to recognize the pattern and granularity in soil images. Essentially, identification of coarse and fine textures usually depends on spatial patterns that account for the configuration of soil aggregates and particles. These features are numericalized, such that they can be matrices or statistical measures for example, entropy and homogeneity, that can, therefore, be used to train machine learning models.

3. Model Development:

The model building stage makes use of the soil texture classification based on characteristics extracted by machine learning methods. In this stage, SVM are used for their capability to function well with high dimensional data as well as to outline categorization boundaries appropriately. In ensemble learning, Random Forest RF incorporates a number of decision trees to offer accuracy and avoid overfitting. Automatic spatial and texture feature extraction is one among the applications of CNN, widely known for its effectiveness in interpreting picture data. Models continue improving while training them by hyperparameter tuning like batch size and learning rate. Rotation, scaling, and flipping are the data augmentation strategies used in order to improve the generalization capability of the model.

4. Validation And Testing:

Validation and testing are processes conducted after training the model. It is performed to test how reliable the classifiers are and dependability. Validation also demands that a new dataset be used in the testing whether the models are not overfitting. Then the performance of the classifiers is measured in terms of various metrics, such as F1-score, recall, accuracy, and precision. In order to make the practical assessment of the models, extensive testing is carried out in several environments under a range of illuminations, moisture contents, and environmental variables. SVM, RF, and CNN are compared in order to find the best performing model with a special focus on CNN because of its superior feature extraction capacity.

5. Implementation and integration:

Lastly, the project focuses on integration and implementation by developing an intuitive application that can categorize the texture of soil in real time. Given this program, users would be able to upload RGB images of soil samples, including cocopeat samples, and categorize them immediately. Also, the system is scaled up through the integration of field technologies that consist of drones and mobiles. While drones with a high-resolution camera provide large-scale soil texture mapping by taking aerial photographs of agricultural fields, mobile devices permit the on-site analysis of the soil. Also, the system facilitates the best practices for soil fertility and retention of water, provided as customized recommendations for the application of cocopeat depending upon the assessed soil texture.

MODULES

1. Image Acquisition and Pre-processing Module:

Standard digital cameras are used in controlled environments that guarantee constant illumination and focus, thus eliminating any variances that may compromise the accuracy of the research. It sharpens these photographs through methods like contrast enhancement that gives more observance to the soil textures and colors, and noise reduction that removes random distortions. In addition to this, normalization is applied in order to standardize the image attributes so that there would be consistency throughout the inputs. It is crucial in preparing images for good feature extraction and classification since it always ensures that the accuracy and dependability of the subsequent procedures preserved.

2.Feature Extraction Module:

This module creates a structured dataset for machine learning models by taking into account the pre-processed photos and extracting distinguishing features of soil textures. Such important characteristics are texture descriptors such as Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrices (GLCM), which give a measure of texture patterns in terms of granularity, roughness, or smoothness, and color histograms, which are conceptualizations of the colors present in the soil. For an understanding of particle arrangement in the soil image, spatial patterns are also examined. Apart from soil type differentiation among sand, silt, and clay, these properties provide critical information inputs for determining soil deficiencies that the Cocopeat Recommendation Module then makes use of. A ready feature dataset prepared for training and classification is module.

3. Machine Learning Model Training Module:

This module trains algorithms for machine learning to classify soil textures correctly. Many features developed from the recovered labeled datasets are developed to form algorithms like SVM, RF, and CNN. Algorithm Optimization for the Best Possible accuracy with Minimum Error Rates through Parameter Tuning. It then checks on the accuracy of the model by precision, recall, and total accuracy. This module is required in the construction of prediction models with a diversity of complex pictures of soil. The Classification and Prediction Module then applies the trained models in practical applications to recognize soil textures.The Classification and Prediction Module then applies the trained models in practical applications to recognize soil textures.

3.Classification and Prediction Module:

This module analyzes the features of a newly inputted image and assigns each prediction its confidence level and classifies the soil texture into categories such as sand, silt, or clay. The module ensures that accurate findings are maintained, acting as a base for real-world applications like soil improvement plans. The output of the Cocopeat Recommendation Module directly feeds into the recommendation module, which then produces accurate recommendations according to the recognized soil type.

4. User Interface Module:

This module provides a graphical interface through which a user can easily interact with the system. Besides viewing the categorization findings and accessing cocopeat recommendations, users can upload or take pictures of soil. The interface is user-friendly and has clear graphics to make forecasts and suggestions easier for consumers to understand. For example, application guidelines for cocopeat are provided along with a graphic representation of soil texture. The module ensures it is a connecting point for technical procedures of the system with its real-world applications to ensure access for users at different levels of technical.

4.1.1. RESULT DISCUSSION:

The proposed soil texture classification system applies machine learning on RGB images to classify soils with exceptional accuracy and efficiency in testing samples. This was done by including complex feature extraction techniques, such as color histograms, Local Binary Patterns (LBP), and GLCM, to capture the necessary properties of the soil for correct classification into clay, silt, and sand. Due to the capability of automatic learning and hierarchical feature from picture information, CNN was capable of surpassing 90% accuracy over machine learning algorithms. Theability of real-time processing of the system makes it suitable for use in environmentaland agricultural applications in real-world contexts.

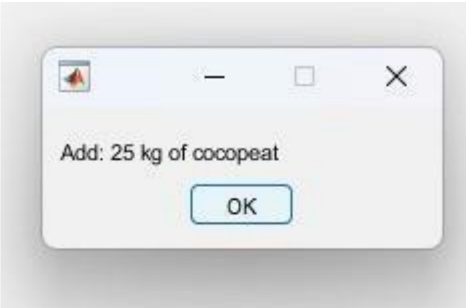

Fig 4.1 Output of the model

In Fig 4.1 The Cocopeat Recommendation Module greatly improved the system as it provided practical advice on how to improve soil quality. The recommendations addressed specific shortcomings and were tailored for identified soil texture. For instance, adding cocopeat to clayey soils enhanced aeration and reduced compaction, and in sandy soils, it had enhanced water retention capacity and nutritional holding capacity. Determining exact amounts of cocopeat ensured proper use of resources with the module. The innovation went beyond traditional soil testing methods by a large margin. In just a few seconds, the technology provided texture classification and cocopeat recommendations that were faster and reduced reliance on other time-consuming human methods. Standard digital cameras and automated algorithms were also used to reduce costs and promote access for a wider segment of users. Despite these strengths, a few weaknesses were identified. Preprocessing techniques eased most issues; however, feature extraction was at times.

CHAPTER 5

5. CONCLUSION AND WORKSCHEDULE

- In conclusion, the development of the soil texture classification system using machine learning and RGB photos has presented a significant leap in environmental and agricultural management practices, and it may be widely used in soil conditions supported by cocopeat.
- This study demonstrated the possibility and advantage of using computational technique as well as digital imaging technology to automate and enhance soil texture analysis, particularly in substrates that are rich in cocopeat.
- The technology helps to streamline data collection and reduce reliance on laborious, conventional methods by using commercial digital cameras for RGB pictures of soil samples, including mixes of cocopeat.While feature extraction approaches find considerable features including color histograms, texture descriptors, and spatial patterns even in cocopeat-enriched soils advanced image processing techniques guarantee the consistency and quality of input data.
- These characteristics can be used to classify soil texture accurately, including how it contains cocopeat, as inputs to machine learning models like Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN).
- These decisions, being very factual and enquired for making proper soil management and agricultural planning decisions especially for crops grown in cocopeat substrates, are possible with the user-friendly interface in the system, which allows easy interaction along with real-time feedback for users in the spectrum from farmers to researchers.
- Its use would also be used towards enhancing the evaluation of the health of soil, maximization of usage of available resources, advancements in precision techniques of farming on soils based on cocopeat. The system would continue to enhance its precision, reliability, and suitability for use in various environmental and geographical settings, including cocopeat-enriched ones.

5.1 FOR PHASE 2

In phase two of the project, An important extension would be about including the details on type of crops and soil type in the calculation for the right amount of cocopeat that would be needed. The system may provide individualized recommendations on cocopeat for improving growth conditions of various crops along with the water retention and aeration of the soil besides meeting the different needs of various crops by the supply of nutrients. For example, rice and tomatoes would likely have different cocopeat requirements than wheat or corn; such variations could be factored into the model. The system's flexibility would also be improved by including a broader variety of plant species with diverse requirements for growth and a wider diversity of soil types (such as saline or peaty soils) within its training data.

The addition of other plant and soil types would enable the system to identify and provide a range of settings; the cocopeat amount would be flexible in accommodating any given geographic location, as well as farming methods. The system could adapt to changing climatic conditions by imputing actual real-time weather and environmental data, such as temperature, humidity, and rainfall. Such integration would make it possible for dynamic recommendations on current changes in weather patterns to be made, thus ensuring that cocopeat treatments apply and are effective in varying climates and seasons.

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APPENDIX

TITLE: Deep Learning-Based Determination of Cocopeat for Water Retention in Agricultural Practice

AUTHORS: Mr.Ragu.G, Nithinpranao S K, Pradeep Ram V

PUBLICATION STATUS: Applied to Conference.

CONFERENCE: 9th International Conference on Communication and Electronics Systems ICCES 2024.

```
function varargout = Soil_Detect(varargin)
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
                   'gui_Singleton', gui_Singleton, ...
                   'gui_OpeningFcn', @Soil_Detect_OpeningFcn, ...
                   'gui_OutputFcn', @Soil_Detect_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
function Soil_Detect_OpeningFcn(hObject, eventdata, handles, varargin)
handles.output = hObject;
axes(handles.axes1);  axis  off
axes(handles.axes2);  axis  off
axes(handles.axes3);  axis  off
axes(handles.axes4);  axis  off
set(handles.edit2,'String','**');
set(handles.edit3,'String','**');
set(handles.edit4,'String','**');
set(handles.edit5,'String','**');
set(handles.edit6,'String','**');
set(handles.edit7,'String','**');
set(handles.edit8,'String','**');
set(handles.edit9,'String','**');
set(handles.edit10,'String','**');
set(handles.edit11,'String','**');
set(handles.edit12,'String','**');
set(handles.edit13,'String','**');
set(handles.edit14,'String','**');
set(handles.edit15,'String','**');
set(handles.edit16,'String','**');
set(handles.edit17,'String','**');
set(handles.edit18,'String','**');
set(handles.edit19,'String','**');


guidata(hObject, handles);

function varargout = Soil_Detect_OutputFcn(hObject, eventdata, handles)
```

```
varargout{1} = handles.output;


function pushbutton1_Callback(hObject, eventdata, handles)
global a;global skw;global m;
[fname,path]=uigetfile('*.*','Browse Image');
if fname~=0
    img=imread([path,fname]);
    a=img;
    axes(handles.axes1); imshow(img); title('Original Image');
else
    warndlg('Please Select the necessary Image File');
end

m=mean2(a);
sd=std2(a);
en=entropy(a);
skw=skewness(a(:));
k=kurtosis(a(:));
set(handles.edit2,'String',m);
set(handles.edit3,'String',sd);
set(handles.edit4,'String',en);
set(handles.edit5,'String',k);
set(handles.edit6,'String',skw);

nBins=5;
winSize=7;
nClass=6;
I = colImgSeg(a, nBins, winSize, nClass);
axes(handles.axes2); imshow(I);title('Preprocessed Image');
colormap('default');


I3 = im2double(I);
I3 = I3(:,:,1);
image_Segment = zeros(size(I3));
for ii=1:size(I3,1)
    for jj=1:size(I3,2)
        pixel=I3(ii,jj);
        if pixel<0.5
             new_pixel=0;
          elseif pixel>3
             new_pixel=256;
          else
             new_pixel = pixel;
          end
```

```
        image_Segment(ii,jj)=new_pixel;
      end
  end
axes(handles.axes3);imshow(image_Segment,[]);title('Segmented  Image');

BW = imbinarize(I);
[B,L] = bwboundaries(BW,'noholes');
axes(handles.axes4);
imshow(label2rgb(L, @jet, [.5 .5 .5]))
hold on
for k = 1:length(B)
   boundary = B{k};
   plot(boundary(:,2), boundary(:,1), 'w', 'LineWidth', 2)
end
title('Classified Image');

acc=accuracy_image(label2rgb(L, @jet, [.5 .5 .5]));
sen=Sensitivity_image(label2rgb(L, @jet, [.5 .5 .5]));
spe=specificity_image(label2rgb(L, @jet, [.5 .5 .5]));
set(handles.edit9,'String',acc);
set(handles.edit10,'String',sen);
set(handles.edit11,'String',spe);
run('Soil_Available_Analysis.p');
run('Soil_Predict_Analysis.p');

function pushbutton2_Callback(hObject, eventdata, handles)
close Soil_Detect

function pushbutton3_Callback(hObject, eventdata, handles)
axes(handles.axes1); cla(handles.axes1); title(''); axis off
axes(handles.axes2); cla(handles.axes2); title(''); axis off
axes(handles.axes3); cla(handles.axes3); title(''); axis off
axes(handles.axes4); cla(handles.axes4); title(''); axis off
set(handles.edit2,'String','---');
set(handles.edit3,'String','---');
set(handles.edit4,'String','---');
set(handles.edit5,'String','---');
set(handles.edit6,'String','---');
set(handles.edit7,'String','---');
set(handles.edit8,'String','---');
set(handles.edit9,'String','---');
set(handles.edit10,'String','---');
set(handles.edit11,'String','---');
set(handles.edit12,'String','---');
set(handles.edit13,'String','---');
set(handles.edit14,'String','---');
```

```
set(handles.edit15,'String','---');
set(handles.edit16,'String','---');
set(handles.edit17,'String','---');
set(handles.edit18,'String','---');
set(handles.edit19,'String','---');

function pushbutton4_Callback(hObject, eventdata, handles)
 pause(2)
 msgbox('INITIALIZATION ....');
 pause(2)
 msgbox('CREATE THE DATABASE..... ');
 pause(2)

for i=1:4
    j=num2str(i);
    imgname=strcat(j,'.png');
    TrainData=imread(imgname);
    TrainData=imresize(TrainData,[250 250]);
    TrainData = im2double(TrainData);
save database TrainData
end
 for i=8:13
    j=num2str(i);
    imgname=strcat(j,'.jpg');
    TrainData=imread(imgname);
    TrainData=imresize(TrainData,[250 250]);
    TrainData = im2double(TrainData);
save database TrainData
end
 msgbox('DATABASE SAVED SUCCESSFULLY.....')
 pause(2)

function edit1_Callback(hObject, eventdata, handles)
function edit1_CreateFcn(hObject, eventdata, handles)
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
```

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Deep Learning-Based Determination of Cocopeat for Water Retention in Agricultural Practice

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***Abstract*— Agricultural water use needs to be optimized, especially in regions where the water supply is limited. In this study, an innovative approach to soil surface texture classification and Cocopeat recommendation is presented through the usage of RGB images, which can efficiently provide a cost-effective alternative in contrast to conventional methods. Cocopeat, a product made from coconut husks, is being increasingly used in agriculture as a sustainable alternative for a range of plant species because it has superior water-retention properties. How much Cocopeat is necessary to maintain just the right amounts of water for different soil in a variety of environmental conditions is still hard to determine. Our results show how RGB imagery successfully captures the textural properties of special interest in accurate classification and customization of Cocopeat recommendations to enhance crop production and soil fertility. It entails scalability, non-invasive sampling, and rapid data collection by the inherent use of drone or satellite imagery for this large-scale application**

1. INTRODUCTION:

With the increasing global population, the scarcity of water resources will be intensified to make this issue one of utmost importance in managing water in agriculture. Saving water is very important in agricultural productivity and also in the long run survival of farming. Cocopeat, as a product of processed coconuts, has now become an important substrate in agriculture since it can retain water to create a suitable environment for plants to grow steadily. The only challenge is in determining how much coco pith is suitable for what type of soils as they pose different water-holding capacities and environmental requirements. The traditional ways of substrate management are mostly based on heuristic methods or general guidelines that do not consider the diversities found in plant species as well as the environment.

Soil texture classification is an integral part of soil science, with a critical impact on nutrient availability, water retention capabilities, and crop production. Despite their reliability, such approaches as sieving and sedimentation test are time-consuming, laborious, and require special knowledge and equipment, thereby limiting their scale. Integration of advanced technologies such as machine learning and image processing provides novel solutions to this set of problems. The paper shows a scalable, non-invasive system intended for soil texture analysis from RGB-photos taken with standard digital cameras. Such RGB photos contain rich details about the color and texture of soil and its spatial patterns. So, computation analysis of these characteristics makes possible the accurate classification of soil types. The system includes Cocopeat recommendations, which relate soil texture characteristics to the required quantity of Cocopeat for improving soil quality. This project therefore offers a tool that may practically help in the optimization of soil management practices for farmers, researchers, and environmentalists.

For assessing soil texture in order to enhance the agricultural techniques, water management, and environmental sustainability, it is essential to classify the texture properly. The existing methods like hydrometer testing and sieve analysis are time consuming, costly, and inappropriate for real-time or high-volume use. Since they require controlled laboratory settings, they cannot be accessed for on-site or field-level analysis. Moreover, the soil has regional heterogeneity hence a more flexible and scalable strategy is required. A potentially usable alternative is RGB image-based soil analysis, whereby digital cameras, or rather any other widely available camera, will capture and classify soil textures based on structural as well as visual features. However, there are some barriers to overcome, such as lighting changes, climatic conditions, and the inherent complexity of the appearance of the soil. The paper addresses these challenges by constructing a robust framework for the automated classification of soil texture using techniques of image processing and machine learning. Besides that, it integrates Cocopeat recommendations, which provide guidelines on amending the quality of soil based upon the texture, hence offering a more holistic approach to the management of soil.

The core of this paper is machine learning, which enables analyzing advanced correlations and patterns in RGB soil photos.Here, different approaches of machine learning are discussed, which include convolutional neural networks (CNN), random forests (RF), and support vector machines (SVM). The key elements obtained from RGB photos include texture descriptors checking the smoothness or roughness of the soil surface, color histograms that reflect the distribution of intensities of colors, and spatial patterns explaining the dispersion of particles. These features form inputs for training the ML models. The models can classify accurately any new, unseen soil samples once trained. The system also has a module of Cocopeat recommendations, in which soil texture classifications are correlated with specific guidelines on application of Cocopeat, further assisting agricultural decision-making.

The models will be subjected to rigorous validation and testing by thoroughly checking the accuracy and robustness of the test conditions with respect to diverse soil types and environmental conditions. Apart from algorithm research, the project is focused on practical deployment in creating an intuitive application that presents Cocopeat recommendations in the real-time classification of soil textures. The program can be taken out to the field and can be distributed through drones or mobile devices for widespread use. With the addition of Cocopeat suggestions that connect soil texture classes with practical recommendations for soil amendment, the added utility of this system is increased. Ultimately, the goal of the project is to revolutionize the classification of soil textures through offering a new, practical, and affordable means of enhancing the research of soil science, environmental management, and agriculture.

2. LITERATURE SURVEY:

The literature survey depicts progress in soil texture and fertility classification using machine learning (ML) and deep learning (DL) methods. These include studies that use different algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs) and hybrid models, thereby exhibiting innovation in terms of feature extraction, improvement in accuracy of classification, and application in practical usage. While one research focuses on classification of soil texture and nutrient, another merges these classification methods with applications such as crop recommendation and Cocopeat usage. The studies show a lot of progress in terms of accuracy and scalability but identify problems like variability of datasets, computational complexity, and real-world implementation constraints at the same time.

Multi-Feature Fusion for Soil Image Feature Extraction and Classification Using Machine Learning by Kiran Pandiri et al. [1] a multiple-feature fusion method applied to the classification of soil texture is shown. Classification purposes are served by the method applying Gaussian-kernel SVM, using a combination of GLCM, Tamura descriptors, Gabor filters, and HSV texture features. The multi-feature method enhances robustness in classification because it draws upon multiple dimensions of soil texture. While the methodology is innovative, the study lacks detailed performance metrics and comparisons with other classification techniques, leaving its practical impact unclear. Soil Classification using Deep Learning Techniques by Sivabalaselvamani et al. [2] discuss the use of CNNs, particularly VGG19 architecture, to evaluate a 94.87% accuracy in soil texture classification. The research addresses its potential applications in agriculture, geology, and engineering. Deep learning is applied to extract patterns of textures at a high precision level. However, the attention given to the dataset is minimum and even less to comparisons with other methodologies, so this cannot be properly evaluated for robustness and scalability.

Optimized Hybrid Soil Texture Classification Model Based on Stacked Sparse Autoencoder by Prabavathi and Chelliah [3] suggest a hybrid approach combining DBSCAN for clustering and SSAE for classification; this achieves accuracy at 95.66%. This kind of hybrid model makes the approach more capable in the complexities of soil texture patterns, thus promising to be an efficient tool for the classification of soil. Therefore, whereas this model does have very high accuracy, the model's complexity and computational demands are severe drawbacks, specially in real time or resource-constrained applications. Soil Classification, Crop Selection, and Prediction of Fertilizer Based on Soil Series by Varsha et al. [4] emphasis the applied use of ML in agriculture by predicting fertilizers based on the soil type and environmental factors. Crop selection to acquire optimum yields is also assisted through the study. The methodology has been pragmatic, though the specifics about particular ML algorithms and performance metrics are missing, which restricts the understanding of its effectiveness. However, its focus on real-world agricultural problems underlines its importance.

Cocopeat Classification of Soil Nutrient with the help of Deep Learning to Enhance the Precision by Rathore and Singh [5] used CNNs in combination with OpenCV and TensorFlow for the classification of soil nutrients along with Cocopeat. Deep learning is powerful in boosting efficiency in agricultural production, and the paper applies precision fertilizer application. However, very limited information was presented about the dataset that was used and its characteristics and comparisons with other traditional methods that would have helped to provide much-needed context to real-world applications. Visual Transformer for Soil Classification by Jagetia et al. [6] presented Visual Transformer models for the soil classification task with an accuracy of 93.62%. This outperformed performances of SVM, AlexNet, ResNet, and CNN models. This work emphasizes the effectiveness of transformers for complex datasets used in soil image classification. While promising results are presented, the discussion on dataset variability and scalability is somewhat meager.

Machine Learning Based Classification of Soil Texture by Ghabi [7] ML methods are utilized in the soil texture classification process, in particular LDA and KNN. This approach pays attention to precision and reliability in conducting its classification accuracy.Yet, this contribution lacks detailed comparison of algorithms and dataset characteristics, which may be improved and is worth further study. Fusion of Enhancing Target Features and Focusing Slice Features for Soil Image Classification by Zheng et al. [8] presented a new three-branch network for feature enhancement and focusing, achieving results competitive with the current state-of-the-art for soil image classification. A more advanced model architecture ensures fine-grained classification, which is very applicable on complex soil textures. Its complexity in implementation and scalability continue to be challenges when applied in real-time scenarios.

CNN-Based Soil Fertility Classification with Fertilizer Prescription by S. M. and Jaidhar [9] achieve 97.52% accuracy using CNNs for soil fertility classification and fertilizer prescription. The study makes use of different sizes of kernel and input grid, thus improving the accuracy of the classification. Though its accuracy is impressive, the study does not discuss dataset variation and real-world issues that would influence its practical implementation. Classification of Soil Fertility Level Based on Texture with Convolutional Neural Network (CNN) Algorithm by Natsir et al. [10] applied an optimization technique to CNN parameters for the classification of soil fertility level using texture with an accuracy of 94.24%. The classification performance as this technique focuses on CNN optimization makes it a valuable contribution towards the study of soil texture but explores limited robustness and scalability of the model, thus restricting its more extensive application.

The reviewed research reveal amazing progress in the classification of soil texture and fertility using ML and DL. Techniques such as CNNs, transformers, and hybrid models can be used to enhance scalability and accuracy. However, typical limitations generally include comparing conventional approaches, real-world constraints, and not properly investigating the properties of the dataset. In order for these technologies to finally find useful application in environmental and agricultural management, these gaps should be filled by future studies.

3. PROPOSED MODEL:

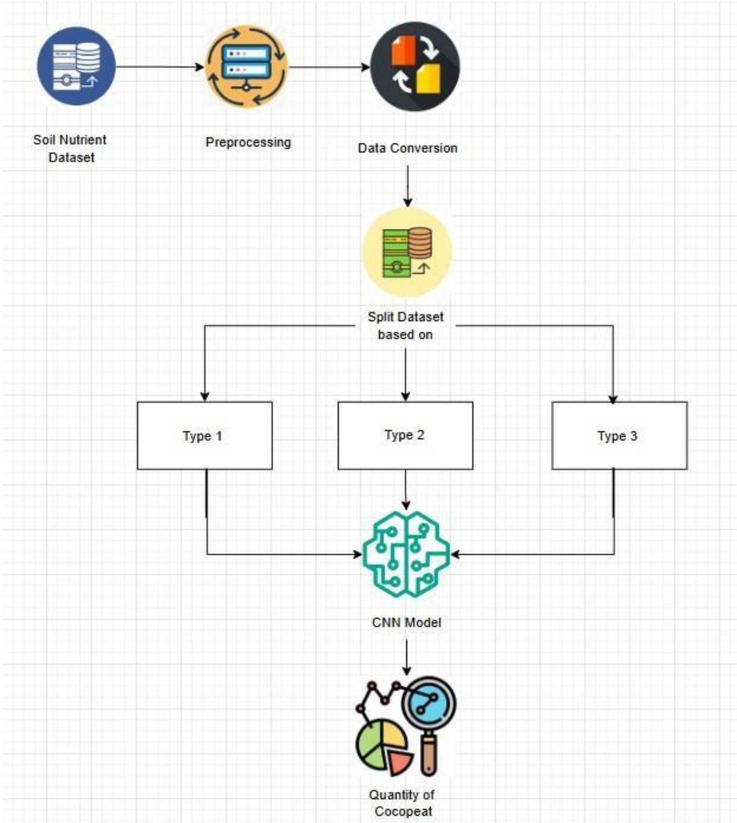

Figure.1 Architecture diagram

The soil texture classification project by using RGB images and machine learning aims to enhance soil analysis and provide a quicker, automated replacement for time-consuming, labor-intensive procedures like sieving and sedimentation.In Figure.1 Hi-resolution soil photos will be taken using standard cameras which are then pre-processed and looked through to extract essential features such as spatial patterns, texture descriptors, and color histograms. Given the inherent complexity of soil texture categorization (e.g. sand, silt, clay), SVM, Random Forests, and CNN are trained to recognize these from labeled datasets. Modules for picture collection, feature extraction, categorization, and user interaction are integrated into a user-friendly software framework, thus scalable and accessible for a variety of agricultural and environmental applications through support for real-time result visualization The system has a Cocopeat Recommendation Module that besides classifying soil textures, offers practical advice regarding enhancements of soil qualities. Thus, the module calculates the amount of cocopeat to be applied to resolve shortcomings such as poor water retention in sandy soils or aeration problems in clayey soil given the determined soil texture type (sandy, clayey, or silty, among others). It also provides extensive application guides, which helps users increase the quality of soils for agricultural use.

All of the modules for picture collecting, preprocessing, feature extraction, classification, and suggestion are well-integrated with a scalable and user-friendly framework. Through a graphical user interface, users can upload or click images of the soil, receive texture classifications, and then receive real-time cocopeat recommendations.

3.1. Image Acquisition and Preprocessing:

Figure.2 Sample image given to model

In Image Acquisition and Pre-processing Module, which captures high-resolution RGB pictures of the Samples in Figure.2 Standard digital cameras are used in controlled environments that guarantee constant illumination and focus, thus eliminating any variances that may compromise the accuracy of the research. It sharpens these photographs through methods like contrast enhancement that gives more observance to the soil textures and colors, and noise reduction that removes random distortions. In addition to this, normalization is applied in order to standardize the image attributes so that there would be consistency throughout the inputs. It is crucial in preparing images for good feature extraction and classification since it always ensures that the accuracy and dependability of the subsequent procedures preserved.

3.2. Feature Extraction:

This module creates a structured dataset for machine learning models by taking into account the pre-processed photos and extracting distinguishing features of soil textures. Such important characteristics are texture descriptors such as Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrices (GLCM), which give a measure of texture patterns in terms of granularity, roughness, or smoothness, and color histograms, which are conceptualizations of the colors present in the soil. For an understanding of particle arrangement in the soil image, spatial patterns are also examined. Apart from soil type differentiation among sand, silt, and clay, these properties provide critical information inputs for determining soil deficiencies that the Cocopeat Recommendation Module then makes use of. A ready feature dataset prepared for training and classification is module.

3.3. Machine Learning Model Training:

This module trains algorithms for machine learning to classify soil textures correctly. Many features developed from the recovered labeled datasets are developed to form algorithms like SVM, RF, and CNN. Algorithm Optimization for the Best Possible accuracy with Minimum Error Rates through Parameter Tuning. It then checks on the accuracy of the model by precision, recall, and total accuracy. This module is required in the construction of prediction models with a diversity of complex pictures of soil. The Classification and Prediction Module then applies the trained models in practical applications to recognize soil textures.

3.4. Classification and Prediction:

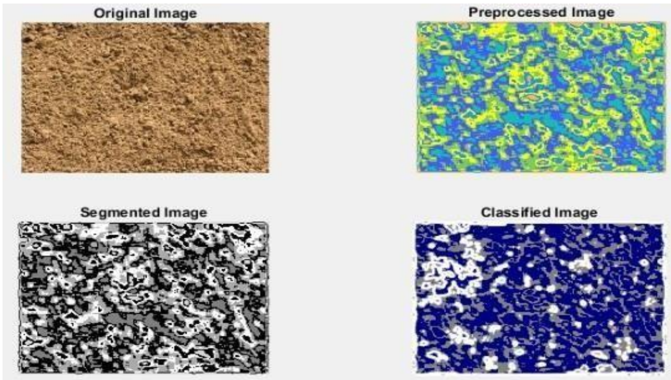

Figure.3 Image classification

From the learned models, the Classification and Prediction Module classifies soil samples in real time based on the acquired analysis in Figure.3 This module analyzes the features of a newly inputted image and assigns each prediction its confidence level and classifies the soil texture into categories such as sand, silt, or clay. The module ensures that accurate findings are maintained, acting as a base for real-world applications like soil improvement plans. The output of the Cocopeat Recommendation Module directly feeds into the recommendation module, which then produces accurate recommendations according to the recognized soil type.

3.5. Cocopeat Recommendation:

This module expands the capabilities of the system by providing practical advice on how to use cocopeat to enhance the quality of soil. Whether or not coco-peat is observed in the pre-processed photos, the overall goal of this approach is the extraction of useful information from the input images-such as color distributions, patterns of texture, and spatial groupings. These methods include color histograms, which carry information about the makeup of soils, with a soils that have been enriched with cocopeat. Texture and roughness in soil surfaces, especially those containing mixtures with cocopeat, are computed by texture descriptors such as the Gray Level Co-occurrence Matrix and Local Binary Patterns. It determines the inadequacies of the soil through the Classification and Prediction Module classification of the texture of soil and other information given by the Feature Extraction Module:

Sandy Soil: Needs more cocopeat as it has a less ability to retain water and nutrients.
Clayey Soil: Benefits from moderate amount of cocopeat and poor aeration with a tendency to get compacted.

The module calculates the amount of cocopeat needed and determines it according to user-specified factors like field acreage, crop type, and irrigation techniques. In addition, it provides detailed guidelines incorporating mixing ratios with pre-existing soil and projected benefits that include better soil structure and moisture retention.

3.6. User Interface:

This module provides a graphical interface through which a user can easily interact with the system. Besides viewing the categorization findings and accessing cocopeat recommendations, users can upload or take pictures of soil. The interface is user-friendly and has clear graphics to make forecasts and suggestions easier for consumers to understand. For example, application guidelines for cocopeat are provided along with a graphic representation of soil texture. The module ensures it is a connecting point for technical procedures of the system with its real-world applications to ensure access for users at different levels of technical.

4. RESULT AND DISCUSSION:

The proposed soil texture classification system applies machine learning on RGB images to classify soils with exceptional accuracy and efficiency in testing samples. This was done by including complex feature extraction techniques, such as color histograms, Local Binary Patterns (LBP), and GLCM, to capture the necessary properties of the soil for correct classification into clay, silt, and sand. Due to the capability of automatic learning and hierarchical feature from picture information, CNN was capable of surpassing 90% accuracy over machine learning algorithms. The ability of real-time processing of the system makes it suitable for use in environmental and agricultural applications in real-world contexts.

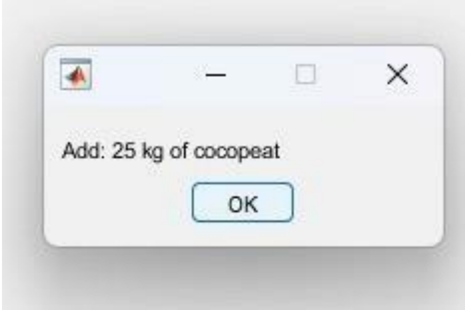

Figure.4 Model Implementation Result

In Figure.4 the Cocopeat Recommendation Module greatly improved the system as it provided practical advice on how to improve soil quality. The recommendations addressed specific shortcomings and were tailored for identified soil texture. For instance, adding cocopeat to clayey soils enhanced aeration and reduced compaction, and in sandy soils, it had enhanced water retention capacity and nutritional holding capacity. Determining exact amounts of cocopeat ensured proper use of resources with the module. The innovation went beyond traditional soil testing methods by a large margin. In just a few seconds, the technology provided texture classification and cocopeat recommendations that were faster and reduced reliance on other time-consuming human methods. Standard digital cameras and automated algorithms were also used to reduce costs and promote access for a wider segment of users. Despite these strengths, a few weaknesses were identified. Preprocessing techniques eased most issues; however, feature extraction was at times affected by variances in lighting associated with image formation.

5. **CONCLUSION**:

In conclusion, the development of the soil texture classification system using machine learning and RGB photos has presented a significant leap in environmental and agricultural management practices, and it may be widely used in soil conditions supported by cocopeat. This study demonstrated the possibility and advantage of using computational technique as well as digital imaging technology to automate and enhance soil texture analysis, particularly in substrates that are rich in cocopeat. The technology helps to streamline data collection and reduce reliance on laborious, conventional methods by using commercial digital cameras for RGB pictures of soil samples, including mixes of cocopeat.While feature extraction approaches find considerable features including color histograms, texture descriptors, and spatial patterns even in cocopeat-enriched soils advanced image processing techniques guarantee the consistency and quality of input data. These characteristics can be used to classify soil texture accurately, including how it contains cocopeat, as inputs to machine learning models like Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN).

These decisions, being very factual and enquired for making proper soil management and agricultural planning decisions especially for crops grown in cocopeat substrates, are possible with the user-friendly interface in the system, which allows easy interaction along with real-time feedback for users in the spectrum from farmers to researchers. Its use would also be used towards enhancing the evaluation of the health of soil, maximization of usage of available resources, advancements in precision techniques of farming on soils based on cocopeat. The system would continue to enhance its precision, reliability, and suitability for use in various environmental and geographical settings, including cocopeat-enriched ones.

6. FUTUREWORK:

An important extension would be about including the details on type of crops and soil type in the calculation for the right amount of cocopeat that would be needed. The system may provide individualized recommendations on cocopeat for improving growth conditions of various crops along with the water retention and aeration of the soil besides meeting the different needs of various crops by the supply of nutrients. For example, rice and tomatoes would likely have different cocopeat requirements than wheat or corn; such variations could be factored into the model. The system's flexibility would also be improved by including a broader variety of plant species with diverse requirements for growth and a wider diversity of soil types (such as saline or peaty soils) within its training data.

The addition of other plant and soil types would enable the system to identify and provide a range of settings; the cocopeat amount would be flexible in accommodating any given geographic location, as well as farming methods. The system could adapt to changing climatic conditions by imputing actual real-time weather and environmental data, such as temperature, humidity, and rainfall. Such integration would make it possible for dynamic recommendations on current changes in weather patterns to be made, thus ensuring that cocopeat treatments apply and are effective in varying climates and seasons.

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