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:

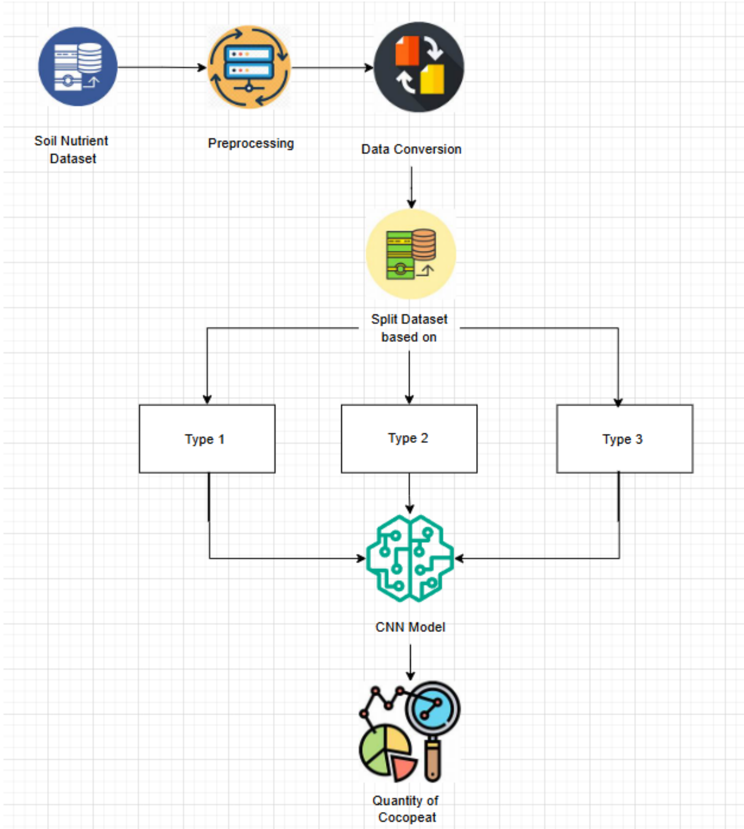

Figure.1 Architecture diagram

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:*

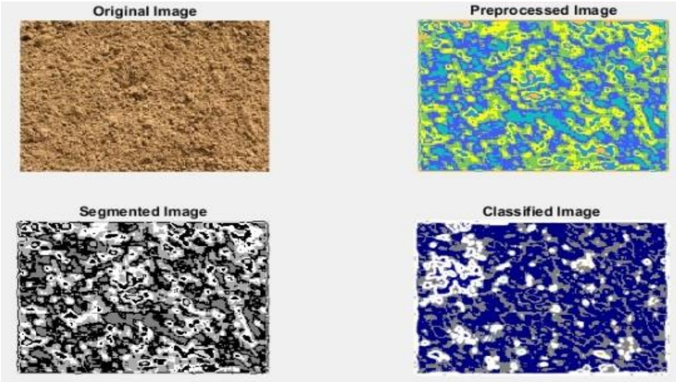

Figure.3 Image classification

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.

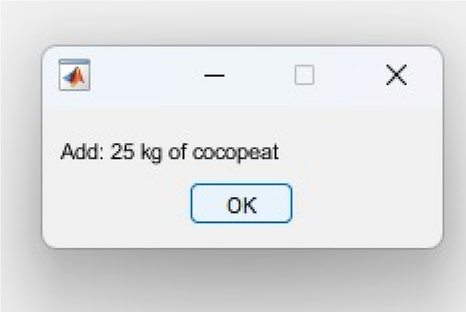

Figure.4 Model Implementation Result

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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