DEEP LEARNING PREDICTIVE MODEL FOR SOIL TEXTURAL ASSESSMENT
/
PAG TUKOY SA URI NG LUPA SA PAMAMAGITAN NG *DEEP LEARNING MODEL*

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ABSTRACT
The distribution of grain sizes in different soil samples is essential for agriculture and geotechnics, providing high-resolution soil maps crucial for land use planning. Traditional methods for soil texture analysis are reliable but often time-consuming and inconsistent. With that, this study aims to create an efficient predictive model for soil texture classification using deep learning techniques. A dataset of 4,556 images was extensively pre-processed and trained, with a model chosen for validation due to its low MSE value of 1.18. The model's performance, evaluated through Precision, Recall, and F1 Score, showed weighted averages of 88%, 78%, and 74%, respectively, and an overall accuracy of 94.56%. Validation using 456 images revealed high accuracy for Sandy and Clayey Soils but varying results for Loamy and Silty Soils. In Trial 1, the model achieved over 91% accuracy for all soil textures, with 100% accuracy for Sandy Soil. However, Trials 2 and 3 exhibited decreased accuracy for Loamy and Silty Soils, with the lowest accuracies at 61.40% and 65.78%, respectively. These results suggest that while the model is effective for certain soil textures, it requires further refinement and additional diverse training data to consistently match the reliability of traditional methods.

ABSTRAK
Ang pagtukoy sa uri ng lupa ay mahalaga sa larangan ng agrikultura at geotechnics. Ito ang nagbibigay ng maayos na mapa na siyang kritikal sa pagpaplano ng paggamit ng lupa. Ang mga tradisyunal na pamamaraan sa pagtukoy nito ay maaasahan, ngunit kadalasang matagal ang proseso at hindi pare-pareho. Dahil dito, ang pagsusuring ito ay naglalayong lumikha ng mabisang modelo para sa klasipikasyon ng uri ng lupa gamit ang makabagong teknolohiya na deep learning. Ang dataset na may 4,556 imahe ay sumailalim sa pag-proproseso, bago ginamit sa paghasa ng iba't ibang modelo, kung saan ang napili para sa balidasyon ay may mababang MSE value na 1.18. Ang bisa ng modelo na sinukat sa pamamagitan ng Precision, Recall, at F1 Score, ay nagpakita ng mga weighted average na 88%, 78%, at 74%, at may kabuuang accuracy naman na 94.56%. Sa balidasyon gamit ang 456 imahe, ipinakita ang mataas na accuracy para sa Sandy (Mabuhangin) at Clayey (Luwad) na lupa ngunit may iba't ibang resulta para sa Silty (Maalikabok) at Loamy (kumbinasyon ng tatlo) na lupa. Sa unang eksperimento, nakamit ng modelo ang 91% accuracy para sa lahat ng uri ng lupa, na may 100% accuracy para sa Sandy soil. Gayunpaman, ang ikalawa at ikatlong eksperimento ay nagpakita ng pagbaba ng accuracy para sa Loamy (61.40%) at Silty (65.78%) Soils. Ipinahihiwatig nito na habang ang modelo ay epektibo sa ilang uri ng lupa, kailangan pa itong mapabuti at dagdagan ng mas magkakaibang datos sa pag-hasa upang ganap na maitatag ang pagiging maaasahan nito.

INTRODUCTION
Soil texture is an important property influencing various physical, chemical, and biological characteristics of soils, which are crucial for agricultural productivity and geotechnical applications. It affects porosity, which determines properties such as water retention, drainage, nutrient availability, and erodibility, thus influencing soil fertility and agricultural productivity (*Chakraborty and Mistri, 2015; Bhattacharyya et al., 2015*). This puts us into the importance of understanding the distribution of soil particles categorized into fine earth (clay, silt, sand) and coarse fragments (gravels, stones) as it is essential in accurate land use planning and soil management.

Up until now, the most practiced method of determining soil texture analysis are the unconventional laboratory method which include sieving, hydrometer analysis, and oven drying. Although widely used, these processes present significant limitations because they are laborious, time-consuming, and prone to inconsistencies. As a result, the entire methods become less efficient in addressing the urgent need for precise soil analysis in light of global challenges like soil degradation and declining fertility (*Food and Agriculture Organization of the United Nations, 2020*).

The answer lies within the recent advancements in soil classification techniques which highlight the growing role of predictive and modelling approaches. Studies have demonstrated the value of statistical models, algorithms, and predictive frameworks, including deep learning and computer vision, in enhancing the accuracy and efficiency of soil texture analysis (*Barman, 2019; Han et al., 2016; Swetha et al., 2020*). These modern methods were proved to have great potential in overcoming the limitations of traditional techniques by enabling fast and consistent assessments of soil properties.

With that, this study aims to contribute to these advancements by developing a deep learning-based approach for soil texture analysis. The objective is to create a model, which could be incorporated into smartphone applications to deliver accurate and timely soil texture assessments. By addressing the inefficiencies of conventional methods, this research seeks to support farmers and land managers, particularly in regions with limited access to technical expertise and laboratory facilities, hence, promoting sustainable soil management and agricultural productivity.

MATERIALS AND METHODS

Sample Preparation

For the training and testing, a similar data set containing pre-determined soil samples from laboratory analysis were used. On the other hand, a different dataset for validation was collected in every town of Nueva Ecija province in Philippines during the year 2023. It underwent into oven-drying at 105°C (±5°C) for 24 hours, before subjected into sieving.

A total of 4,556 images were taken for training and testing via random sampling, equally distributed under different soil texture categories (Clayey, Silty, Sandy, and Loamy). Since a learning model can generally work with 100, 500, or even 10,000 images (*Barkved, 2022*), the study's sample size was within the limit.

Ideally, a good accuracy in machine learning is anything greater than 70%; and, anything in 70-90% accuracy is not only ideal, but is also realistic (*Rosenbacher, 2022*). However, in soil related studies, the lowest accuracy obtained was 58% via Random Forest classifier (*Dornik et. al., 2018*), and several 100% accuracy in some researches (*Morais et. al., 2019, Han et. al., 2016*). Therefore, this study considered that any result as long as it is within the stated range of existing and published studies, would be considered acceptable and valid.

The soil samples were then taken using a smartphone with 108-megapixel resolution during daylight in a landscape camera-orientation and distance of 0.25 m vertically on top to capture the entire soil sample. A random splitting of data with ratio of 80:20 was used for training and testing. This is known as the rule of thumb in split training and testing of data in python – the language used in training the model.

Another randomly selected samples from dataset for validation (accounting to 10% of the total images used in training and testing) was used in order to avoid biasness that could happen in using similar set of data for validation (*Baheti, 2021*). There is no specific data split requirement in training, testing, and validation of soil classifications involved in machine learning. For example, *Anadan et. al. (2021),* used different train-test-validate data split ratio on their two different studies (70-15-15 in 2021 using CNN and 60-20-20 in 2022 using hybrid CNN-LMO algorithm), while *Han et. al., (2016),* used 10% of the total soil samples for their testing. With that, the researchers decided to follow the general rules governing data splitting of machine learning methods.

Table 1

Distribution of dataset for Training, Testing, and Validation

PRE-DETERMINED SOIL (4,556 SOIL SAMPLE IMAGES)		**SOIL GATHERED IN NUEVA ECIJA, PHILIPPINES (NOT YET DETERMINED)**
TRAINING (80%)	TESTING (20%)	VALIDATION (10% of training and testing)
3645	912	456

Training and Testing

The images were placed in separate folders for training and testing (training data, testing data) in order to have an organized segmentation of data used in designating labels for training and testing purposes. Each soil texture determined through laboratory analysis are also separated by folder. Studio Visual Code was the used IDE (Integrated Development Environment) for editing of codes as it supports and allows various usage of programming languages without the need to switch for editors. It served as the center and the most crucial element of establishing the predictive model for soil texture assessment.

The images underwent the process of Augmentation, Pre-processing with Hue, Saturation, and Value (HSV) extraction before subjecting to training.

To capture the hidden layers, Convolutional Neural Network was used. Structuring the CNN architecture of the study include Input Layer, Convolutional Layer, Pooling Layer, Flatten Layer, Fully Connected (Dense) Layers, and Output Layer. On the other hand, YOLO is employed for classes identification, brightness training, and for utilizing the Open Source Computer Vision Library (OpenCV).

Performance Evaluation and Data Analysis

In soil classification, the best matrix that showed the most favorable result was confusion matrix; this is both for binary and multiclass (*Srivastava et al., 2021*). This matrix is represented by rows and columns, wherein the actual labels are written in rows, and the predicted labels are in columns – a widely adopted convention in field of machine learning and statistics. True positive and true negative means correctly classified labels, while false positive and false negative represents the incorrectly classified labels.

In a confusion matrix, the performance metrics such as Precision, Recall, Accuracy, and F-measure were generated. Precision measured the fraction of the estimated soil patterns in a positive class that the model accurately identified as positive:

$$p = \frac{tp}{tp+fp} \tag{1}$$

where:

p denotes the precision, while tp implies the true positive, and fp represents the false positive.

Meanwhile, recall defines the ratio between positive soil patterns to the correctly classified soil patterns. It can be computed by the following formula:

$$r = \frac{tp}{tp+tn} \tag{2}$$

where:

r denoted recall, while tp and tn represents true positive and true negative, respectively.

Accuracy, on the other hand, is the ratio of right prediction made, over the number of examples evaluated:

$$acc = \frac{tp+tn}{tp+fp+tn+fn} \tag{3}$$

where:

acc represents the accuracy, while tp and tn defines the true positive and true negative, and fp and fn implies the false positive and false negative, respectively.

Finally, the f-measure represents the harmonic mean between the values of precision and recall. The best evaluation for these metrics should be one or closer to one.

$$fm = \frac{(2*p*r)}{p+r} \tag{4}$$

where:

f_m represents the f-measure, while p and r represent precision and recall.

During the training stage, the Mean Squared Error (MSE) can be determined which represents the difference between estimated solutions and the ones that are preferred. A low value of MSE is required to get better training results.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2 \tag{5}$$

where:

MSE means the mean squared error, while P_i is the predicted value, and A_i is the desired value.

Research Design and Statistical Analysis

In order to prove the consistency of the developed model when it comes to predicting soil textures, the study employed Analysis of Variance (ANOVA) under Complete Randomized Design (CRD) as treatment method to the gathered data. The process here is similar to the procedure of t-test. However, t-test can only determine differences between the means of two groups, while ANOVA can do with more groups *(Ardiansah et. al., 2021 & Zhang et. al., 2024)*.

Therefore, this method is appropriate to identify the significant differences among three (3) validation sets for each independent metrics (accuracy, precision, recall, and F1 score). The conditions were set to reject the null hypothesis if p value result is less than 0.05. Since the researches wanted the readings across all validations to be consistent, the null hypothesis was set to: *there is no significant difference in the performance metrics observed across three validations*.

RESULTS

Training of Model

The training was commenced using 4,556 images which underwent into several trainings and re-trainings in order to optimize the result. The final training underwent 100 epochs with 179 steps per epochs and Batch size of 30.

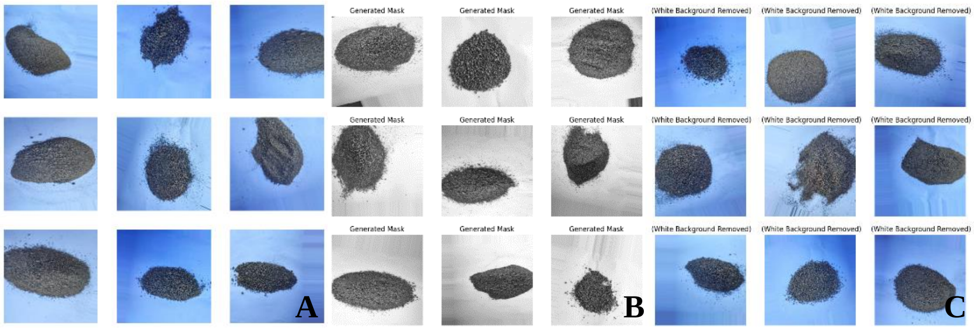

Fig. 1 – Pre-processed Images

A – Raw Image; B – Masked Image; C – Background Removed Image

The image samples underwent to pre-processing procedures and feature extractions (shown in Figure 1) which include masking, removing of image background, resizing of images into consistent resolutions in order to ensure uniformity of data; pixel normalization into 255 pixels; augmentation of data to increase the diversity of training data; cropping of images to focus on region of interest; color space conversion; and then noise reduction to clean and denoise the images before feeding the datasets to the model training.

Several models have been developed throughout the training as a result of utilizing different techniques to achieve the highest accuracy possible. In order to determine the predictive model to be chosen, the MSE of each model have been determined as shown in Figure 2.

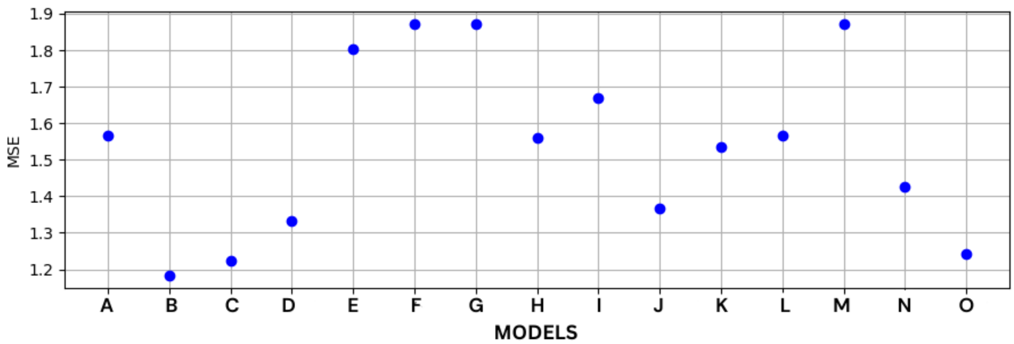

Fig. 2 – MSE of Different models developed throughout the course of training

Among the different training models, model B showed the lowest MSE value (1.18), hence it was considered to be the final model to be evaluated.

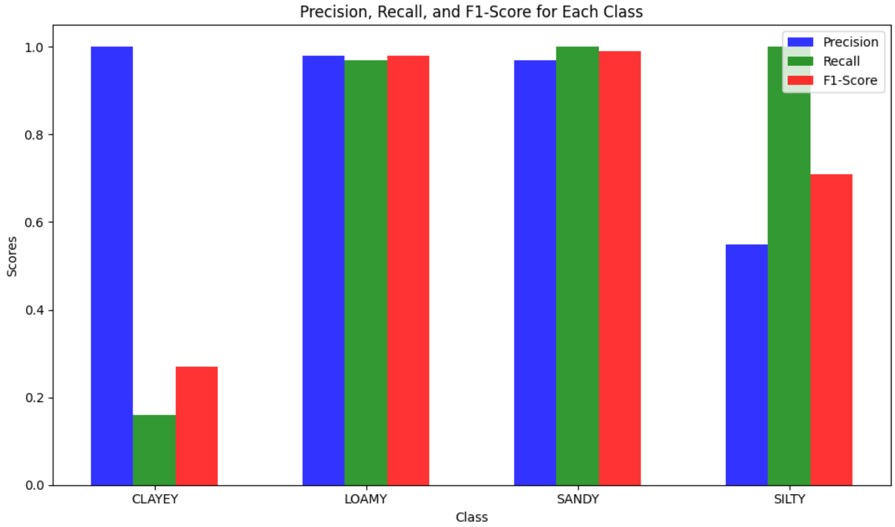

Fig. 3 – Precision, Recall, and F1 Score for each class of the best model

The different results of evaluation matrices for each class were shown in Figure 3. The weighted average of each evaluation matrices during the training of the model was 88% for Precision, 78% for recall, and 74% for the F-score. The overall accuracy of the training on the other hand, was 94.56%.

The interface of the developed predictive model (Figure 4) was run in an open-source app framework called *Streamlit*. It is a Python framework used in creating visualization for machine learning data. The interface was made user-friendly with written instructions on how to operate.

User will upload an image through the 'browse' menu, and click 'classify' to obtain results (the predicted soil texture and some common suitable crop recommendations).

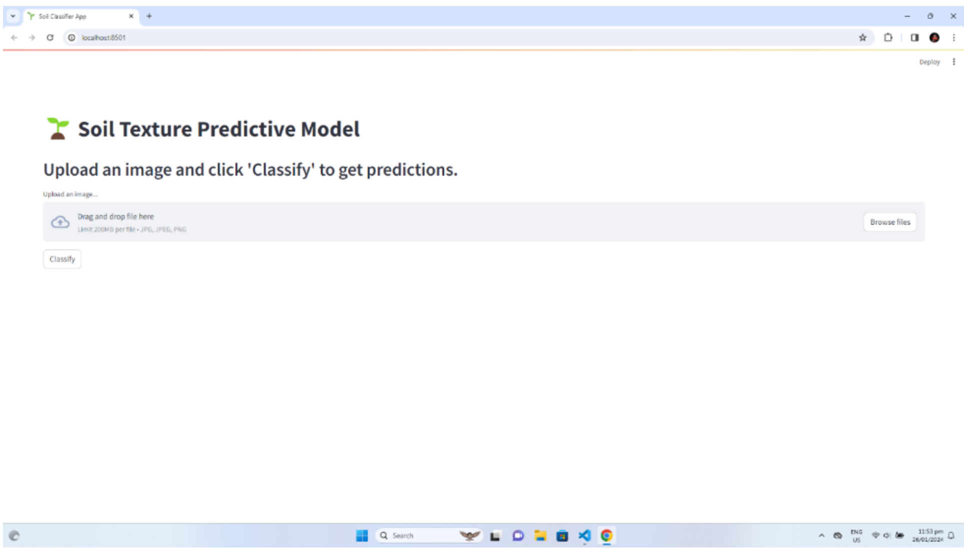

Fig. 4 – Interface of the predictive model in a local host

Actual Validation

For actual validation of data, three (3) validations were done in order to have a comparison of metrics gathered (accuracy, precision, recall, and F1 score). The validation images were 10% of the total number of images (*Baheti, 2021*).

Since a total of 4,556 images were used in training and testing, 456 images were used for validation (114 images for each soil texture categories). Shown in Table 2 is the summary of three validations made to determine if there are significant differences among the yielded results.

Table 2

Average Performance Metrics results across three validations

	ACCURACY	PRECISION	RECALL	F1 SCORE
VALIDATION 1	0.96	0.96	0.96	0.96
VALIDATION 2	0.83	0.85	0.83	0.85
VALIDATION 3	0.79	0.78	0.79	0.79

The study considered four different levels (metrics) such as the Accuracy, F1 Score, Precision, and Recall. There are 12 observations in total, all of which were read and used in the analysis. Using Statistical Tool for Agricultural Research, the result of analysis was shown in Table 2.

Table 3

ANOVA Analysis output

Source	Df	Sum of Squares	Mean Square	F value	Pr(>F)	CV (%)	Data Mean
Metrics	3	0.0001	0.0000	0.00	0.9996		
Error	8	0.0629	0.0079				
Total	11	0.0630				10.28	0.8625

The results of statistical analysis made revealed that there are no significant differences found among the metrics. This is because the p-value = 0.9996 is not less than 0.05, hence, the null hypothesis will not be rejected. It suggests that all metrics perform similarly with respect to the response variable. A coefficient of variance (CV) value of 10.28% or 0.1028 also suggested that the variation with respect to the mean is relatively low because a CV that is less than one is universally considered low variance. This means that the data points of performance metrics were relatively close to the mean value, hence, resulting in a smaller variation.

The data means (0.8625) for Accuracy, F1 Score, Precision, and Recall, which measures the central tendency, or the average value of overall data points, are very close, reinforcing the ANOVA result of no significant differences among the metrics. It shows that the data points exhibit relatively low variability around the mean value. As a result, there is a consistent level of performance across the different trials, with relatively minor fluctuations.

The analysis of the result reveals significant insight towards the performance of model in testing and actual validation of data. The testing was initiated with a dataset comprising of 4,556 images that underwent several iterations, trainings, and re-trainings to produce the best result. In order to determine which model has the best training result, the MSE should be low (*Srivasta et. al., 2021*) ranging from 1-10 for typical image processing that has pixel value range of 255. Since Model B has the lowest MSE value (1.18) as shown in Figure 2, it was the model chosen to be subjected into validation.

The performance of the final model was assessed using the standard evaluation metrics (*Srivasta et. al., 2021*): Precision, Recall, and F-score (Figure 3). The weighted averages for these metrics during training of the model were 88% for Precision, 78% for Recall, and 74% for F1 Score. These metrics, along with an overall accuracy of 94.56%, demonstrated the developed model's capability in correctly classifying the images. The accuracy of this model is inside the range of several studies related to soil image classification which utilized deep learning techniques.

Yu et. al., (2019), utilized 3D-CNN system that explored configurable liquid crystal filters (LCTF) which resulted in 99.59% accuracy. *Morais et. al. (2019),* achieved an impressive 100% accuracy in classification and prediction using Digital Image Processing and MIA classifier. Other studies such as *Dornik et. al., (2018),* and *Mengistu & Alemayehu, (2018),* resulted in 58% and 89.7 accuracies respectively, which can be noted as much lower accuracies compared to the study.

For actual validation, 456 images (10% of the total dataset) were used, divided equally across the four soil texture categories (*Baheti, 2021*). Three validation runs were conducted to compare the performance metrics. The results showed varying degrees of accuracy, precision, recall, and F1 score across the validations (Table 2). Validation 1 exhibited the highest consistency with an accuracy, precision, recall, and F1 score of 0.96, while validations 2 and 3 showed lower but still acceptable performance levels.

To show how the developed model performed against the laboratory assessed samples, the number of predictions was listed in Table 4 below.

Table 4

Comparison of readings from Developed Predictive Model to the Laboratory Assessed samples

Laboratory Method Assessment Trial 1		**Predictive Model Assessment Trial 1**		
Texture	**No. of Sample**	**Texture**	**No. of Predictions**	**Correct Predictions**
Sandy Soil	114	**Sandy Soil**	**114**	**100%**
Silty Soil	114	**Silty Soil** Clayey Soil Loamy Soil	**109** 3 2	**95.61%**
Clayey Soil	114	**Clayey Soil** Silty Soil	**104** 10	**91.23%**
Loamy Soil	114	**Loamy Soil** Silty Soil	111 3	**97.37%**
Laboratory Method Assessment Trial 2		**Predictive Model Assessment Trial 2**		
Texture	**No. of Sample**	**Texture**	**No. of Predictions**	**Accuracy**
Sandy Soil	114	**Sandy Soil** Loamy Soil Silty Soil	**107** 4 3	**93.86%**
Silty Soil	114	**Silty Soil** Loamy Soil Sandy Soil	**96** 11 7	**84.21%**
Clayey Soil	114	**Clayey Soil** Silty Soil	**100** 14	**87.72%**
Loamy Soil	114	**Loamy Soil** Sandy Soil Silty Soil	**76** 5 33	**67.67%**
Laboratory Method Assessment Trial 3		**Predictive Model Assessment Trial 3**		
Texture	**No. of Sample**	**Texture**	**No. of Predictions**	**Accuracy**
Sandy Soil	114	**Sandy Soil** Loamy Soil	**112** 2	**98.24%**
Silty Soil	114	**Silty Soil** Loamy Soil Clayey Soil Sandy Soil	**70** 30 9 5	**61.40%**
Clayey Soil	114	**Clayey Soil** Silty Soil	**101** 13	**88.60%**
Loamy Soil	114	**Loamy Soil** Silty Soil Sandy Soil	**75** 33 6	**65.78%**

The model showed high accuracy for Sandy and Clayey Soils. On the other hand, Loamy and Silty soils have greater number of incorrect readings that varied across all soil textures. In Trial 1, the model achieved over 91% accuracy for all soil textures, with a perfect 100% accuracy for Sandy Soil. In Trial 2, accuracy declined for Loamy and Silty Soils, with Silty Soil reaching a low of 67.67%. Trial 3 showed further drops for Loamy and Silty Soils, with accuracies of 61.40% and 65.78%, respectively, while maintaining a high accuracy of 98.24% for Sandy Soil.

These findings indicate that while the developed model performs well in prediction of certain soil textures, it still needs refinement and additional data for diverse training in order to achieve a consistent and similar reliability reading of traditional methods.

CONCLUSIONS

The analysis of the model's performance reveals both strengths and areas for improvement for the study. Trained on a dataset of 4,556 images, the model was chosen for validation due to its lowest MSE value of 1.18. During training, the model achieved strong evaluation metrics, including 88% Precision, 78% Recall, 74% F1 Score, and an overall accuracy of 94.56%, which aligns with other deep learning studies in soil image classification. However, the validation of 456 images in comparison to predetermined soil textures showed variable results, especially for Loamy and Silty Soils, with significant accuracy drops in Trials 2 and 3.

Despite that, the ANOVA analysis still indicated no significant differences among the evaluation metrics, and a coefficient of variation of 10.28% which suggested consistent performance overall. While the model demonstrated high accuracy for Sandy and Clayey Soils, its performance for Loamy and Silty Soils was inconsistent, indicating the need for further enhancement and more varied training data. In conclusion, the model showed strong potential for certain soil textures but still requires additional development to achieve consistent and reliable performance comparable to traditional laboratory methods.

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