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Performance of Convolutional Neural Network for Classifying Soil Moisture Level based on In-Situ RGB Soil Surface Images

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ABSTRACT

Computer vision offers a promising method for soil moisture assessment especially for real-time field monitoring where sensor-based measurements are limited. This study evaluates the performance of a traditional Convolutional Neural Network (CNN) and ResNet-50 architecture for classifying soil moisture levels directly from in-situ surface images. The research involved 200 field-captured images and corresponding moisture data from a rainfed agricultural area. The models were trained with datasets grouped into two, three, and four moisture categories to test performance under varying complexity. The results showed poor model performance, characterized by high instability and severe overfitting across all experiments. Model accuracy for the traditional CNN significantly decreased from 0.513 to 0.256 as the number of classification categories increased and from 0.487 to 0.205 for ResNet-50. High RMSE values from 0.433 to 0.507 further confirmed substantial prediction errors. This finding highlights the limitation of RGB-based in-situ imagery for soil moisture classification, where environmental variability dominates the visual signal. It also suggests that soil moisture-related features are not sufficiently distinguishable under uncontrolled field conditions. The study concludes that the high variability of direct field images due to factors like inconsistent lighting, illumination, and the presence of non-soil objects is a primary obstacle to accurate classification. Future studies should implement advanced pre-processing techniques such as segmentation to reduce illumination noise.

1. INTRODUCTION

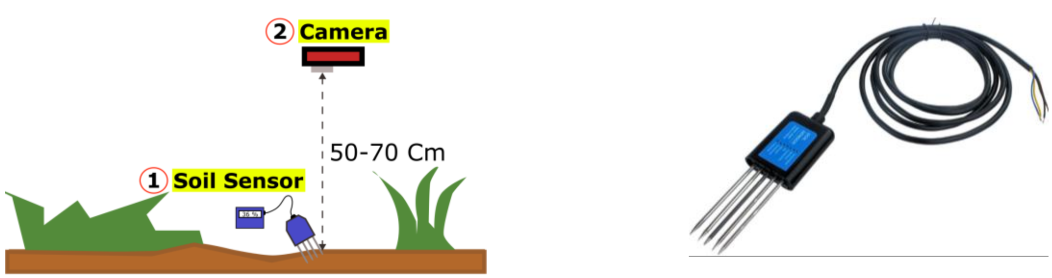
One of the most critical soil parameters in agriculture is soil moisture content. Soil moisture content, especially in shallow soil, is an ecohydrological natural resource that regulates important land surface mechanisms and influences agricultural productivity and management practices (Rasheed *et al*., 2022). The soil surface appearance can indicate a specific condition of the soil. The change in soil color can indicate the existence of organic matter, soil moisture, and soil pH (Alaoui *et al*., 2020). Visual soil assessment is the most common way to determine soil condition. The ASTM D2488 standard procedure is often used to visually assess soil parameters like color, shape, and angularity to describe soil conditions (ASTM International, 2017). With the advancement of technology, the visual assessment and observation usually conducted by the eye can now be done by computer vision. The most well-known computer vision technique is the convolutional neural network. Convolutional Neural Networks (CNN) represent a specific deep learning approach designed for classifying visual data. CNN is a network architecture for deep learning that learns directly from data, eliminating the need to perform feature extraction. The extraction process uses filters, resulting in feature maps highlighting specific input image features (Ghosh *et al*., 2019).

Supervised machine learning models such as CNN has been widely used to identify and classify visual objects. CNN has the ability to extract spatial features from images, making it a robust vision-based classifier (Chen *et al*., 2024). The main advantage of CNNs is that pooling layers help reduce computational load. The pooling layer is a technique to reduce the size of the CNN output. It reduces the number of network parameters and eases computational resources, but it also keeps the accuracy and precision (Jeong & Na, 2024). Besides that, many pre-trained CNN data architectures can be used nowadays with various characteristics of the fully connected layer library, such as GoogleNet, ResNet, AlexNet, and VGGNet. It also makes CNNs more popular for image classification (Basha *et al*., 2020). Some research has shown good results of CNN implementation for soil classification. Ansari & Gautam (2024) has tested CNN accuracy to classify soil moisture content based on images collected from the internet which were non-field, controlled images, differing from this study's in-situ approach. The accuracy can achieve 73% after tuning the hyperparameters. However, CNNs are prone to overfitting due to an imbalanced dataset. So, parameter tuning is often needed to augment the complexity of the model (Hemdan & Al-Atroush, 2025). The low accuracy of image classification of 24% due to data imbalance was obtained by Qi *et al*. (2024), but after normalizing the data, the accuracy increased to 67%. One drawback of CNNs is that they can be computationally demanding. This research aims to explore the performance of soil moisture level classification using CNNs based on direct image capture of the soil surface. Most existing studies rely on controlled or pre-processed image datasets, which may not represent real-world field conditions. Direct image capture of the soil surface will be more applicable in fields. However, it has a risk of vulnerability to noise and perturbations. The observation in this study will emphasize how CNNs can classify the level of soil moisture content based on soil surface images taken directly in the field. In this study, the performance of the classification model based on direct images of the ground surface in the field without any arrangement will be investigated, and the results will be compared with similar existing studies.

2. MATERIALS AND METHODS

2.1. In Field Data Acquisition

The field data acquisition was conducted from May to June 2024 at observation points, which consist of soil surface image and soil moisture data collection. The observation points cover the agricultural area in Poncogati Village, Sub-district of Curahdami, Bondowoso Regency, Indonesia. The soil texture in this area is sandy clay, the soil type is mostly regosol, and most of it is a rainfed agricultural area. A soil surface image is taken first before soil moisture data acquisition, as shown in Figure 1. The soil moisture data is taken using a soil sensor Modbus RS-485, as shown in Figure 1(b). Soil measurements were taken at a depth of approximately 25 cm to 30 cm to determine the condition of the topsoil, following the sensor manufacturer's recommendations (ComWinTop limited, 2023).Soil surface image acquisition was conducted directly in the field using a cellphone camera with an OV48B camera sensor with 48 Megapixels featuring a 0.8-micron pixel size in 0.5-inch optical format. The camera is directed perpendicular to the soil surface with a distance to the surface between 50 cm and 70 cm, as shown in Figure 1(a). The height range is 50 cm to 70 cm based on our field



(a) (b)

Figure 1. The illustration of (a) measurement method for sensor data acquisition and ground surface photos and (b) the appearance of soil sensor 5 probes Modbus RS485

data collection trials. This range is the most comfortable for taking photos in the field, without requiring excessive body bending. Images were taken under natural light between 7:00 and 10:00 AM to minimize lighting variations.

2.2. Convolutional Neural Networks

There are 200 input data points, consisting of soil moisture content and soil surface image data collected from fields. In fact, there was initially a larger volume of image data, but this has been further filtered to retain only those images of sufficient pixel resolution and image size to meet the specified moisture content classification criteria. It is hoped that the model will be able to distinguish more effectively between the specified moisture content categories. As shown in Table 1, each run of the CNN model includes three different dataset groupings. The dataset grouping considers data distribution in each soil moisture content range to avoid data imbalance. The CNN model was developed based on traditional CNN architecture, and the ResNet-50 architecture was used to compare both results.

Table 1. Distribution of data quantity in each dataset grouping

Number of group	Dataset Grouping for CNN modelling					Total number of data
2	**Soil Moisture ranges**	**0%-20%**	**21%-100%**			
	Number of data	*104*	*96*			*200*
3	**Soil Moisture ranges**	**0-15%**	**16-30%**	**31-100%**		
	Number of data	*64*	*67*	*69*		*200*
4	**Soil Moisture ranges**	**0%-10%**	**11%-20%**	**21%-40%**	**41%-100%**	
	Number of data	*50*	*54*	*45*	*51*	*200*

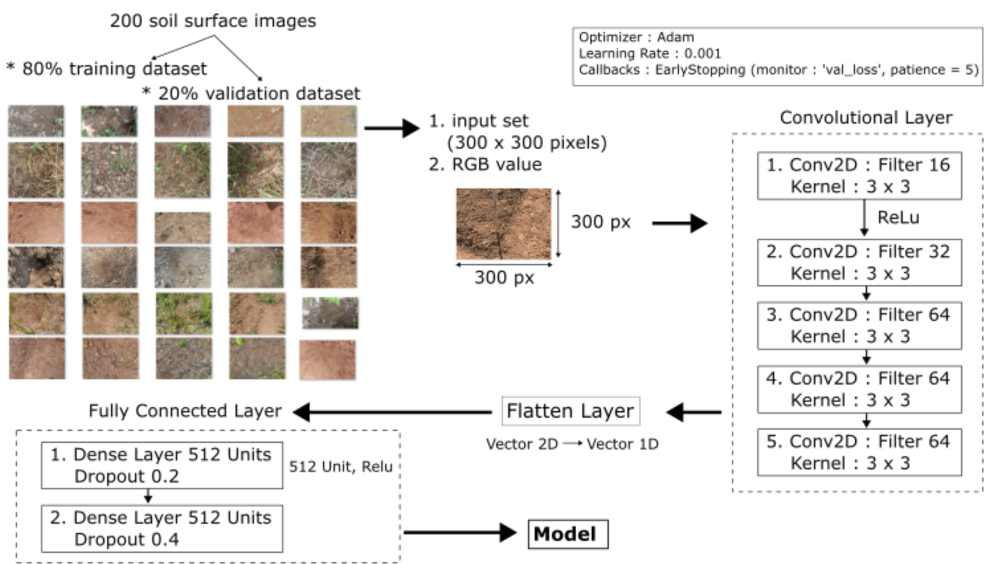


Figure 2. Architecture model of traditional CNN

The architecture of the traditional CNN model, as shown in Figure 2, consists of five convolutional layers, also including dropout for regularization, preventing overfitting. A traditional CNN (Convolutional Neural Network) refers to an artificial neural network architecture for image processing that has a linear or sequential design. This means that image data is processed sequentially, moving in a single direction from the first layer to the last, without any skip connections or complex branching (Omar, 2020). This traditional CNN architecture refers to research conducted by Hegazi *et al.* (2021), which produced a fairly high model accuracy of soil moisture classification based on data from Sentinel-1. The ResNet-50 model was implemented using TensorFlow Keras' pre-trained library within Google Colab. ResNet-50 is an extremely deep CNN architecture to overcome the degradation problem and decrease accuracy, using residual learning (Celano, 2021). Unlike traditional CNNs, the ResNet-50 architecture features skip connections or shortcut connections that create residual blocks. These shortcuts allow the output of a layer to bypass several preceding layers and be added to the output of a deeper layer. This technique enables analysis using deeper layers. ResNet -50 uses deeper layers (50 layers), so it should be better than traditional CNN architecture. The CNN model experiment was prepared and run on the Google Colab platform.

2.3. Data Preparation

All input image datasets are set to 300 x 300 pixels, 300 dpi, and must have red, green, and blue (RGB) values. Data augmentation was performed before the images were trained using the model by applying various geometric transformations randomly to the input images. Random augmentation performed in this study includes vertical and horizontal shifts of up to 20%, maximum rotation of up to 20%, maximum shear of 20%, maximum flip of 20%, and maximum zoom of 20%. This augmentation effectively increases the training dataset virtually. This augmentation helps the model become more robust and prevents overfitting because the model is exposed to a wider variety of the same data. From 200 datasets, 20% of the total data was used as a validation dataset, and the rest was used as a training dataset.

2.4. Analysis

The accuracy and loss training validation graph evaluated the model's performance. Accuracy training validation can explain the proportion of correct predictions, while loss training validation shows how big the model's prediction error is. Furthermore, the performance is also captured from the accuracy, log-loss test results, and root mean square error (RMSE). Log-loss is used to measure how well a classification model predicts the probability of an event. The RMSE value in this study measures the average magnitude of the error between the model's predicted value and the actual classification value.

3. RESULTS AND DISCUSSION

The example of input images captured in the field is shown in Figure 3, where the majority of the soil color is reddish brown, and some are blacker and darker. The soil images are captured directly in the field without any preliminary treatment. Each image was resized to 300×300 pixels and lighting was not standardized. Some roots or grass leaves are sometimes visible in the input image. The input image data used for modelling is truly in situ and represents the actual ground surface conditions. The previous study indicated that soil color parameters such as color coordinates, metric

(a) (b) (c) (d)

Figure 3. The examples of soil image in some soil moisture levels of (a) 0-10%, (b) 11%-20%, (c) 21%-40%, (d) 41%-100%

lightness, metric chroma, and Munsell value were negatively correlated with the moisture content. However, the correlation becomes weaker on the black soils since color changes become less visible (Bhadra & Bhavanarayana, 1997). Soil color provides a complex picture of the soil. It is influenced not only by soil moisture but also by mineral and organic content (Jackson, 2020). This complexity makes it difficult for CNN to perform classification, as indicated by the accuracy and loss training validation graph, as shown in Figure B. The performance of the model can be revealed from the graphs. The graphs plot the loss and accuracy of the model on the training dataset and validation dataset over each epoch. Epoch refers to one complete pass of the entire training dataset through the learning algorithm. It draws on how well the model is learning and the generalization ability (Kulkarni *et al*., 2025). The accuracy and loss training validation graph of all models in Fig 4 have varying numbers of epochs. The number of epochs varies because of the implementation of the early stopping technique by detecting the change of validation loss value (Val loss). If the last Val loss does not improve during 10 epochs, then the model will end the training process. Val loss shows the performance of the CNN model working on data that the model has never received during the training process.

Based on data in Figure 4, there is an indication of high instability during the training process, as indicated by high fluctuation in accuracy and loss training validation graph on all CNN models. There are indications of overfitting since the training accuracy is higher than training validation, as shown clearly in Figure 4 (a), (b), and (e). The training loss tends to be more stable than the very volatile validation loss, indicating severe overfitting, as seen in Figure 4 (c). The performance looks worse in the model with four categories of soil moisture levels. Validation Accuracy is very low and fluctuates around 0.2-0.3, as seen in Figure 4 (c) and (d). Overall, all models have a barrier to convergence and achieving stable performance, even though hyperparameter adjustments, regularization techniques, and data augmentation have been carried out in this study. There is an indication that the distinguishing features from RGB images of the soil surface at each soil moisture level are not strong enough to be captured by the CNN model.

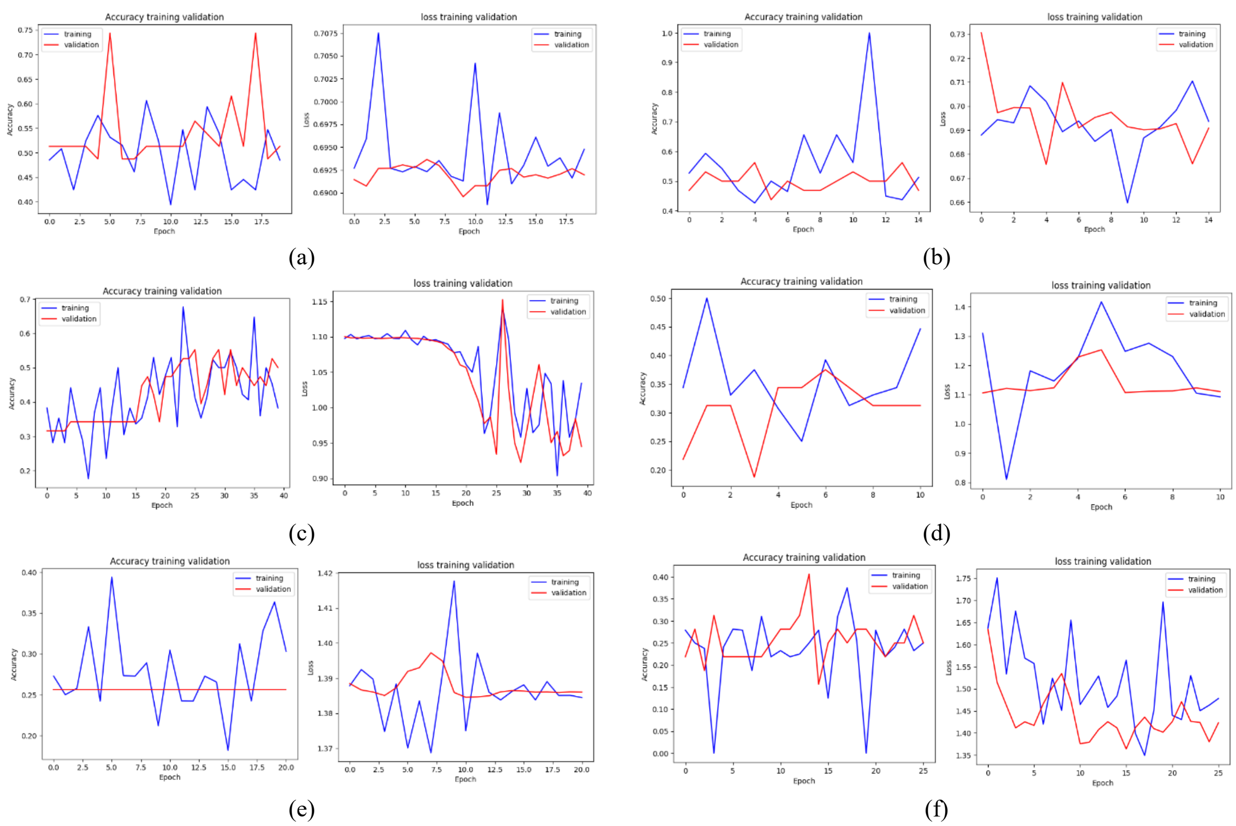


Figure 4. Performance of the model using traditional CNN with (a) 2 categories, (c) 3 categories, and (e) 4 categories of soil moisture level; And using ResNet-50 Model with (b) 2 categories, (d) 3 categories, and (f) 4 categories of soil moisture level

It is clearly seen that the accuracy decreases significantly as the number of soil moisture categories increases, both for traditional CNN and ResNet-50, as shown in Table 2. Log Loss increases as the number of categories increases, indicating that the model's confidence in its predictions is decreasing and its uncertainty is increasing. In general, ResNet-50 shows slightly lower log loss in the 2 and 3 soil moisture level categories but slightly higher in the four soil moisture level categories. The RMSE does not show a consistent pattern of increase or decrease, such as accuracy and log loss, but it tends to vary depending on the number of categories and model architecture. However, all models indicate that the RMSE value is too high, between 0.433 and 0.507, indicating that the average error made by the models is very large. The increasing number of categories leads to a greater imbalance in data validation, as shown in Table 3. This imbalance is reflected by certain F1-scores dropping to 0 in models with 3 and 4 categories, indicating the model fails to recognize some classes. In contrast, models with 2 categories have more balanced and reliable performance, especially the CNN ResNet-50 model. These facts suggest that more categories require more data.

Table 2. Model performance metrics

Number of Soil Moisture Categories	Model Architecture					
	Traditional CNN			ResNet-50		
	Accuracy	Log loss	RMSE	Accuracy	Log loss	RMSE
2	0.513	0.687	0.497	0.487	0.683	0.498
3	0.316	1.326	0.507	0.368	1.117	0.476
4	0.256	1.383	0.433	0.205	1.405	0.436

Table 3. Precision, recall, and F1-score metrics of the CNN model

Number of Soil Moisture Categories	Soil moisture range	CNN Resnet 50				Traditional CNN			
		Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
2	0%-20%	0.62	0.65	0.63	20	0.41	0.45	0.43	20
	21%-100%	0.61	0.58	0.59	19	0.53	0.32	0.33	19
3	0%-15%	0.4	0.44	0.42	9	0	0	0	9
	16%-30%	0	0	0	7	0.33	0.14	0.2	7
	31%-100%	0.29	0.29	0.29	7	0.3	0.86	0.44	7
4	0%-10%	0.46	0.75	0.57	8	0.46	0.12	0.14	8
	11%-20%	0	0	0	5	0	0	0	5
	21%-40%	0.17	0.17	0.17	6	0.17	0	0	6
	41%-100%	0	0	0	4	0	1	0.38	4

It is clearly seen that the accuracy decreases significantly as the number of soil moisture categories increases, both for traditional CNN and ResNet-50, as shown in Table 2. Log Loss increases as the number of categories increases, indicating that the model's confidence in its predictions is decreasing and its uncertainty is increasing. In general, ResNet-50 shows slightly lower log loss in the 2 and 3 soil moisture level categories but slightly higher in the four soil moisture level categories. The RMSE does not show a consistent pattern of increase or decrease, such as accuracy and log loss, but it tends to vary depending on the number of categories and model architecture. However, all models indicate that the RMSE value is too high, between 0.433 and 0.507, indicating that the average error made by the models is very large. The increasing number of categories leads to a greater imbalance in data validation, as shown in Table 3. This imbalance is reflected by certain F1-scores dropping to 0 in models with 3 and 4 categories, indicating the model fails to recognize some classes. In contrast, models with 2 categories have more balanced and reliable performance, especially the CNN ResNet-50 model. These facts suggest that more categories require more data.

Beyond technical limitations, the findings of this study highlight a more fundamental issue in RGB-based soil moisture classification using in-situ imagery. The results indicate that soil moisture signals are not dominant features in uncontrolled field conditions, where variations in illumination, soil composition, and surface heterogeneity introduce significant noise. This contrasts with previous studies conducted under controlled environments, where lighting and sample conditions are standardized, allowing models to achieve high accuracy. RGB images are often affected by lighting. Lighting influences the intensity and angle of light, thereby altering the raw RGB values of pixels even though the actual colour of the object remains the same. Changes in lighting can cause irregularities in intensity, colour and texture, making it difficult for CNNs to distinguish between real and false edges (Song *et al*., 2024). Furthermore, CNN models often struggle to classify soil heterogeneity accurately based solely on RGB imagery due to the limitations of low spectral resolution, the visual similarity between soil types, and the fact that they only cover the soil surface, whereas soil conditions are also influenced by deeper, unseen soil layers (Pan *et al*., 2026).Therefore, the poor performance observed in this study should not be interpreted merely as model failure, but rather as evidence of the limitation of RGB imagery for representing soil moisture in real-world agricultural settings.

Even Bhadra & Bhavanarayana (1997) said that soil color has a negative correlation with the soil moisture level. However, it turns out it's not that easy to classify based on in situ RGB images of the soil surface. The risk of using in-situ soil surface images to classify soil moisture is that there are many factors that affect the results of soil surface images in the field, like lighting, illumination, and the presence of non-soil objects. Other than that, Soil color relates not only to soil moisture but also to soil organic matter and mineral content (Fu *et al*., 2020). A similar study to predict soil moisture content based on soil surface images was conducted by Kim *et al*. (2023) and showed better results since the soil image acquisition data was collected from indoor soil that had been arranged in mold. The accuracy of the CNN model in that study can achieve 100% for 216 x 216 resolution. The non-soil objects have been disposed of from the soil samples and prepared to have more equivalent lighting and illumination. These results highlight that, despite poor initial performance, soil surface imagery can still be promising if illumination and non-soil objects are controlled. Model failure indicates that soil moisture signal is not dominant in uncontrolled environments. This research also hints that the more complex architecture does not guarantee more convergent results. The traditional CNN gives better accuracy than the ResNet-50 model for binary and four categories of soil moisture level classification. Considering that data augmentation and regularization techniques have been carried out, this overfitting can be influenced by complex architecture models of ResNet-50, high variability of soil surface data, and insufficient data pre-processing. The pre-processing process, like image segmentation to minimize the effects of excessively varied lighting, illumination, and the presence of non-soil objects, can be proposed for the next improvement step.

In addition to the challenges discussed above, this study is also constrained by the relatively limited dataset size, consisting of only 200 samples. Such a dataset is relatively small for training deep learning models, particularly convolutional neural networks, which typically require large-scale data to achieve stable generalization. Furthermore, although efforts were made to distribute the data across different soil moisture categories, the grouping process introduces a potential risk of class imbalance, especially as the number of categories increases. This imbalance is reflected in the inconsistent performance metrics and the occurrence of zero F1-scores in several classes. Therefore, future research should consider expanding the dataset significantly, both in terms of sample size and diversity, to improve model robustness and generalization capability under real field conditions.

4. CONCLUSIONS

Significant challenges to classifying soil moisture levels based on in-situ surface images in achieving accurate and stable classification. Model performance sharply decreased as the number of moisture categories increased, which was confirmed by declining accuracy, rising log-loss, and high Root Mean Square Error (RMSE) values across all tests. The primary challenge identified was severe overfitting, driven by high data variability from inconsistent field conditions like lighting, the presence of non-soil objects, texture, organic matter content, and physicochemical properties, even after data augmentation was applied. Interestingly, the more complex ResNet-50 architecture did not guarantee superior performance over the traditional CNN. These findings underscore that direct field imagery requires advanced pre-processing. These findings emphasize that RGB-based in-situ soil imagery alone may not be sufficient for reliable soil moisture classification in real-world conditions. The study provides important evidence that environmental variability can overshadow moisture-related visual features, highlighting the need for more robust sensing approaches or controlled imaging techniques. In addition, the relatively small dataset size and the potential class imbalance across categories may have contributed to the unstable model performance. Future studies should focus on collecting larger and more balanced datasets to improve model generalization. Other focus is image segmentation to isolate relevant soil features and minimize environmental interference, which is essential for improving model reliability.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
HMS	✓	✓	✓						✓		✓	✓		
SAB								✓		✓				
EBK										✓				✓
DEK				✓					✓		✓			
IP									✓				✓	

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

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