

SOIL MOISTURE PREDICTION FOR BITTER GOURD CROPS: PRECISION FARMING WITH DEEP LEARNING

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Abstract: Precision agriculture is transforming the way farming is carried out by helping farmers use resources more efficiently while improving crop yields. One of the most important factors in this process is soil moisture content, since the amount of water required varies depending on the crop, the type of soil, temperature, and humidity in the field. Traditional methods of measuring soil moisture are often slow, labor-intensive, and rely on specialized equipment. With the rise of modern technologies, however, farmers can now turn to deep learning, computer vision, and even simple smartphone cameras to make soil monitoring faster and more practical. In this study, two advanced transfer learning models—VGG16 and InceptionV3—were used to predict soil moisture levels from images of the soil surface taken with smartphones. These pre-trained deep learning models were fine-tuned to recognize subtle patterns in soil images that indicate moisture levels. The results are highly promising: VGG16 achieved an accuracy of 98.25%, while InceptionV3 slightly outperformed it with 99.48%. Such strong results show that soil moisture can be assessed with remarkable accuracy simply through image-based techniques, without the need for expensive sensors or manual measurements.

Keywords: Soil Moisture, Transfer Learning, Precision Agriculture, Deep Learning.

1. INTRODUCTION

Soil is one of the most fundamental natural resources for sustaining life, as it supports the growth of food crops and provides other essential needs for the global population. With the world's population continuing to rise, the optimal and efficient use of natural resources has become more critical than ever. Among the many factors that influence agriculture, soil moisture plays a central role. It acts as the key link between the atmosphere and the land, governing the transfer of both water and energy to agricultural fields. Soil moisture refers to the relative amount of water contained within the soil, a parameter that is not static but continuously fluctuates over time. These fluctuations are influenced by multiple factors, including irrigation practices, evaporation of water from the soil surface, natural rainfall patterns, and local weather conditions. In addition, soil moisture levels are closely tied to changes in climate, reflecting variations in temperature, precipitation, and other environmental parameters [1]. Understanding these patterns provides valuable insight into how crops respond to their surrounding environment and helps farmers make informed decisions. For instance, in the case of cultivating bitter gourd, soil moisture requirements vary across different stages of growth. Observations suggest that after seeding, the soil must remain consistently wet for the first two weeks to ensure proper germination and establishment of the plant. Beyond this stage, maintaining soil in a moderately moist or "partially-wet" condition is sufficient until the crop is ready for harvest. Monitoring soil moisture under these conditions ensures that the crop receives neither too much nor too little water, which directly impacts both yield and quality. In this context, the present study focuses on tracking and analyzing soil moisture variations specifically for bitter gourd cultivation. By doing so, it aims to provide a clear understanding of the ideal water requirements of the plant, helping farmers adopt more precise irrigation practices. Figure 1 illustrates a bitter gourd crop cultivated under these soil moisture conditions, highlighting the practical importance of monitoring soil moisture to maximize productivity while conserving valuable water resources.



Figure. 1 Bitter Guard cultivation in the field

It is well established that variations in climatic parameters strongly influence fluctuations in soil moisture, making it one of the most sensitive indicators of climate change. Predicting soil moisture largely depends on understanding its correlation with different climatic variables. However, since these factors are often inconsistent, random, complex, and nonlinear in nature, modelling soil moisture becomes a challenging task. To address this, many researchers have employed Support Vector Machines (SVMs) to build prediction models based on historical meteorological data [2]. In the realm of machine learning, one particularly powerful approach that has gained popularity is transfer learning. This technique allows a model that has already been trained on one task to be adapted for another related task. Essentially, the knowledge gained from one problem is transferred to improve learning in another, enabling the model to generalize more effectively. The benefits of transfer learning are especially valuable in real-world scenarios. Its three main advantages are: reduced training time, enhanced neural network performance, and the ability to work with limited datasets. Training a deep learning model from scratch typically requires vast amounts of data, which is not always feasible to collect. Transfer learning addresses this issue by leveraging pre-trained models that already possess strong feature extraction capabilities. By fine-tuning these models for a new application, researchers can build robust and accurate machine learning systems even with relatively small amounts of training data. In particular, for applications such as image classification, transfer learning has emerged as a powerful solution, bridging the gap between data scarcity and the need for high-performance predictive models.

2. RELATED WORKS

The accurate prediction of soil moisture enabled by advanced deep learning methods demonstrates the strong potential of data-driven models to enhance our understanding of environmental dynamics while guiding efficient water resource management strategies. Several recent studies have explored this area, showcasing the diversity of techniques available for soil moisture assessment and prediction. For example, the authors of [3] provide a comprehensive survey on the use of image processing for soil moisture estimation. Their work discusses different approaches to image acquisition, the processing algorithms involved, and the associated challenges, while highlighting the promise of non-destructive techniques in agricultural and environmental applications. Similarly, in [4], a sophisticated method was proposed to retrieve soil moisture data at high spatio-temporal resolutions by integrating machine learning with CYGNSS and SMAP satellite observations. This integration of remote sensing with data-driven approaches represents a significant advancement for accurate environmental monitoring. In [5], researchers introduced a complex-valued neural network to enhance soil moisture forecasting, demonstrating how innovative neural architectures can improve predictive accuracy. Complementary to this, [6] explored the application of image processing techniques for understanding soil moisture dynamics, while [7] compared autoregression and neural network models for soil water content prediction. Work in [8] presented an optimized neural-supported model aimed at improving sustainable agricultural practices through accurate soil moisture forecasting. Zanetti et al. [9] contributed a novel method combining color images with artificial neural networks to estimate soil moisture in tropical soils, underscoring the practical value of vision-based techniques. Wang et al. [10] extended this by rigorously evaluating the performance of multiple deep learning models for soil moisture forecasting, offering important insights for hydrology and environmental management. Li et al. [11] further advanced this field by demonstrating the effectiveness of deep learning and transfer learning for daily soil moisture prediction using SMAP satellite data, with strong implications for hydrological applications in China. Beyond these, research in [12] highlighted the role of convolutional neural networks (CNNs) and transfer learning in revolutionizing soil water content prediction, particularly in

the context of smart farming for rural India. Similarly, [13] showcased how IoT technologies, coupled with transfer learning, can enhance irrigation efficiency by enabling precise soil moisture forecasting. In [14], a method that uses image-based interpolation of soil surface imagery to accurately estimate soil water content is presented. A root-zone soil moisture prediction system using deep learning models based on hyperspectral images captured via unmanned aerial vehicles is presented [15]. Taken together, these studies present a wide spectrum of approaches, ranging from image processing and remote sensing to advanced neural network architectures and IoT-based solutions. Collectively, they emphasize the importance of adopting innovative techniques for soil moisture assessment, laying a strong foundation for sustainable agriculture, efficient water management, and informed environmental decision-making.

3. METHODOLOGY

Dataset description

The collected dataset from the farm consists of 3945 soil images. For the creation of the dataset, soil images of different moisture contents were shot from an agricultural farm located in Kodhandapuram village, Thiruvannamalai district, Tamilnadu. Figure.2 shows the farm where the soil images were captured. The dataset is split into a training set and test set comprising 2982 training images and 963 testing images respectively as shown in Table 1. Classification of soil images is performed for three classes: dry, partially-wet or wet as shown in Figure. 3.



Figure. 2 Agricultural farm where soil images were captured

Table 1: Dataset split up

Subset	No of images	Percentage
Training data	2928	75.6
Test data	963	24.4

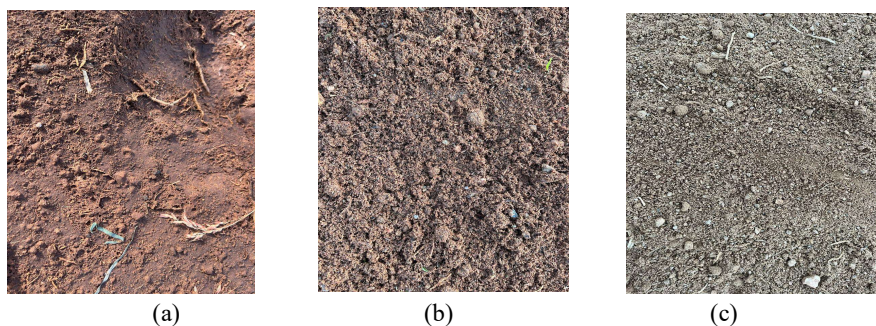


Figure. 3 (a) Wet (b) Partially-wet (c) Dry Soil images

Data Preprocessing

Data preprocessing is a critical step in developing reliable prediction models, as it ensures that the dataset is standardized and consistent for training. In this study, the dataset was carefully prepared using data augmentation techniques to improve both the quality and diversity of the input samples. Multiple variations of the original soil images were generated, effectively expanding the dataset and reducing the risk of overfitting. The augmentation process involved applying several transformations, such as rotation, width and height shifts, shear adjustments, zooming, and horizontal flipping. These modifications introduced natural variability into the training data, helping the model become more robust and capable of recognizing soil moisture patterns under different orientations and perspectives. Ultimately, this preprocessing strategy enhanced the generalization ability of the deep learning models, making them more accurate and reliable for real-world soil moisture prediction.

Model description

In the proposed approach, the power of transfer learning was harnessed by employing deep convolutional neural networks based on well-established architectures such as VGG16 and InceptionV3. Transfer learning enables these networks to leverage knowledge acquired from the broad and diverse ImageNet dataset, enhancing their performance on the targeted soil image classification task. By initializing the models with weights learned from ImageNet, valuable features and hierarchical representations acquired during the object detection training were capitalized on. This strategic use of transfer learning enables the models to be adapted and excel in discerning wet, dry, and partially-wet soil conditions with increased efficiency and accuracy, benefiting from the prior knowledge embedded in the pre-trained architectures. The concept of transfer learning is depicted in Figure. 4.

The pre-trained CNNs being employed in this work are:

1. VGG16
2. Inception V3

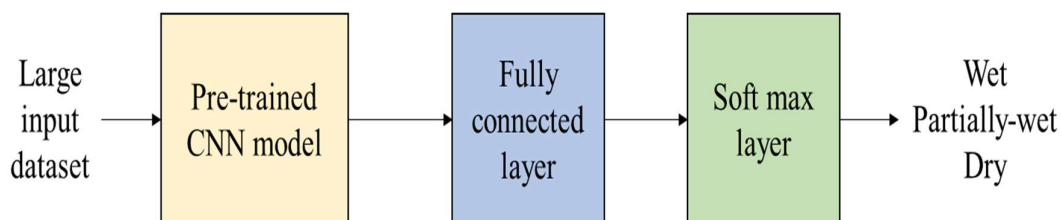


Figure. 4 Architecture of Transfer Learning Model

VGG16 Architecture

VGG16 is a deep convolutional neural network developed by Oxford's Visual Geometry Group in 2014. Its architecture as shown in Figure. 5, has 16 layers, including 13 convolutional and 3 fully connected layers, using 3×3 filters throughout. The network stacks convolutional and max-pooling layers before classification, with around 138 million parameters. Despite being computationally heavy, it is effective for feature extraction and widely used in transfer learning for applications like medical imaging, agriculture, and soil moisture prediction from images.

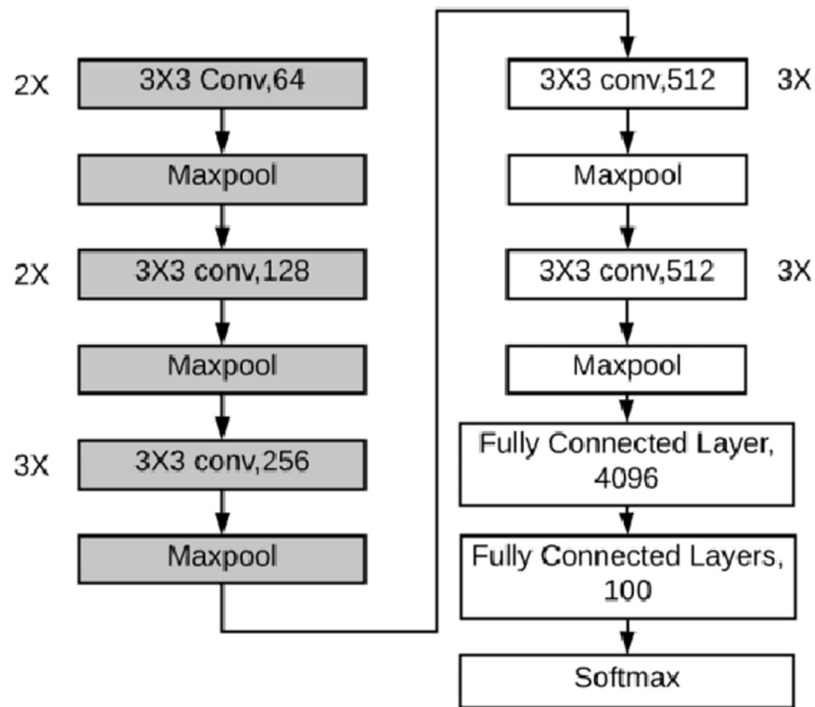


Figure.5. VGG16 Model architecture

Inception V3

Inception V3, part of Google's Inception architecture family, is well-known for its balance of complexity and efficiency. It is a powerful pre-trained convolutional neural network (CNN) model widely used in transfer learning. The architecture of Inception V3 is shown in Figure. 6. Researchers often leverage Inception V3's learned features and weights as a starting point for new tasks, fine-tuning the model on smaller, task-specific datasets. This approach enables improved performance while requiring less data and computational resources, making Inception V3 a popular choice for a variety of computer vision applications.

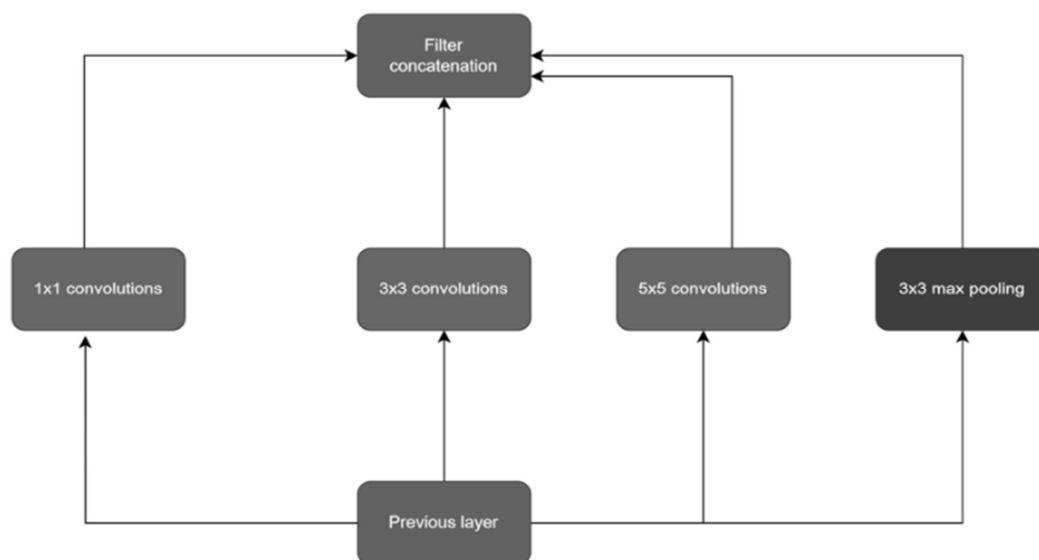


Figure.6. Inception V3 model architecture

4. RESULTS

In this section, the performance of the transfer learning models, VGG16 and Inception-V3 are compared and evaluated based on the performance metrics such as accuracy and loss. In addition, visual aids such as classification reports, confusion matrix plots, classification reports, accuracy graphs, and loss graphs are generated to gain insights into the behaviour and performance of the model.

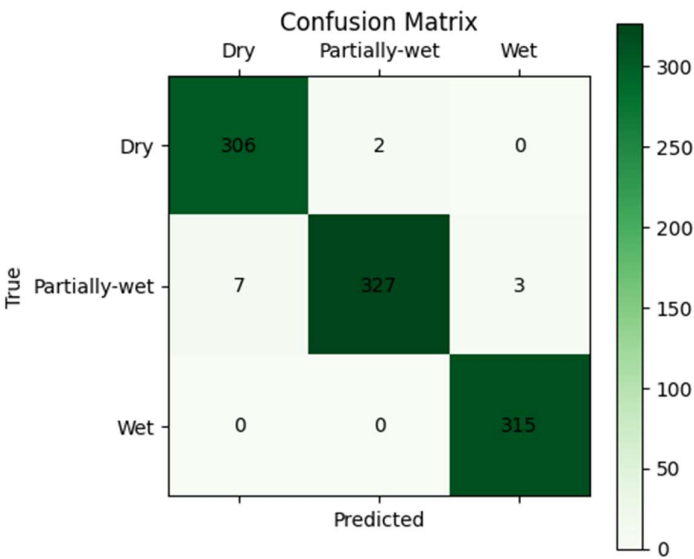


Figure. 7. Confusion matrix of VGG16.

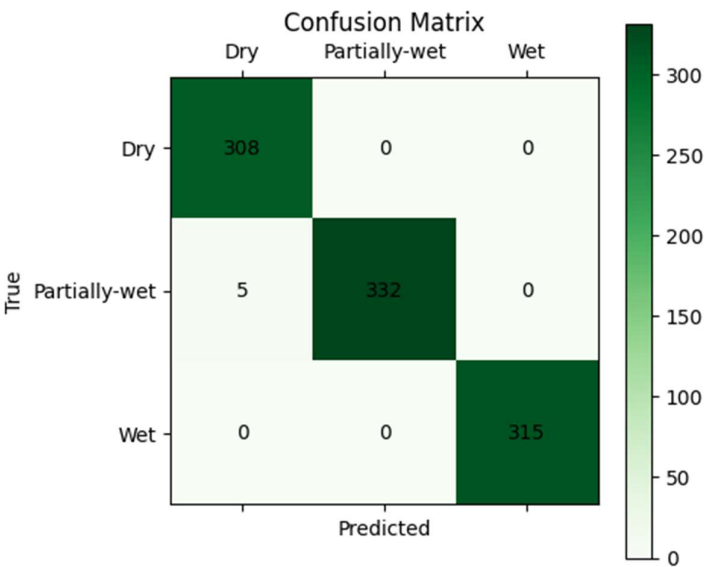


Figure. 8. Confusion matrix of Inception V3

Table 2: Comparison of accuracy and loss

Model	VGG16		Inception V3	
	Training accuracy (%)	Training loss	Testing accuracy (%)	Testing loss
Training data	99.12	0.0184	98.25	0.6557
Test data	99.65	1.6988e-06	99.48	0.0806

Table 2 shows the accuracy and loss during training and testing in VGG16 and Inception-V3 respectively.

A confusion matrix is a table used in machine learning and statistics to evaluate the performance of a classification algorithm. It provides a summary of the predicted and actual class labels for a set of data points. Figure. 7 and Figure. 8 show the confusion matrix values of Inception V3 and VGG16 respectively.

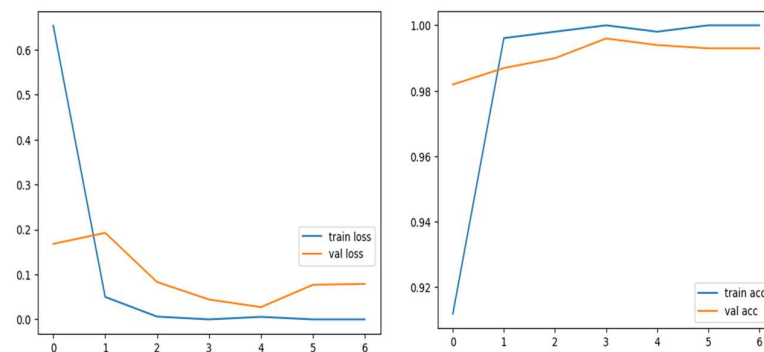


Figure. 9. Accuracy vs Epoch and Loss vs Epoch graphs of Inception V3

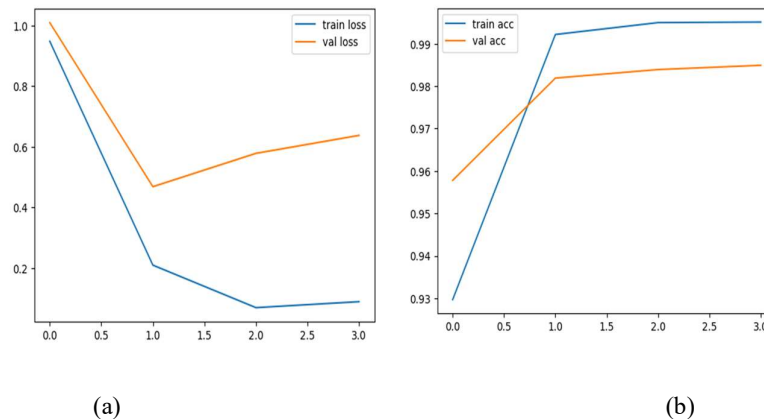


Figure. 10. Accuracy vs Epoch and Loss vs Epoch graphs of VGG16

Accuracy vs. Epoch and Loss vs. Epoch graphs provide crucial insights into the training dynamics of a model, helping to assess convergence, overfitting, and overall performance during the learning process. Figure .9 and Figure.10 show the Accuracy vs Epoch and Loss vs Epoch graphs of Inception V3 and VGG16 respectively.

A classification report is a summary detailing the performance metrics, including precision, recall, and F1 score, for each class in a classification model, offering a comprehensive evaluation of its predictive capabilities. From Table 3 and Table

4, Inception-V3 has outperformed VGG16 in all performance parameters, due to its superior feature extraction capabilities, optimized hyperparameters, and a more favourable alignment of pre-trained weights with the dataset characteristics.

Table 3: Classification report of VGG16

Class	Precision	Recall	F1 score
Dry	0.98	0.99	0.99
Partially-wet	0.99	0.98	0.99
Wet	1.00	1.00	1.00

Table 4: Classification report of Inception V3

Class	Precision	Recall	F1 score
Dry	0.99	1.00	0.99
Partially-wet	1.00	0.99	0.99
Wet	1.00	1.00	1.00

5. CONCLUSION

Soil moisture has a big impact on crop growth. Both the agricultural and hydrological sectors rely significantly on soil moisture information. Therefore, a thorough understanding or precise predictions of future soil moisture conditions can help plan irrigation, improve the efficiency of agricultural water use, and predict yields. This study focuses on precise techniques for reliably forecasting soil moisture for bitter guard cultivation. Soil images captured from the agricultural farm are preprocessed and segmented into classes of dry, partially-wet and wet. In order to achieve enhanced precision and sensitivity in detecting soil moisture levels, transfer learning techniques are applied. An accuracy of 98.25% and 99.48% is achieved in VGG16 and Inception V3 respectively for soil moisture prediction. This soil moisture prediction combined with an automatic irrigation schedule could help in smart bitter gourd farming.

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