International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 6, December 2025, pp. 5667~5678
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i6.pp5667-5678

Fine-tuning pre-trained deep learning models for crop prediction using soil conditions in smart agriculture

Praveen Pawaskar[1,2], Yogish H K[1], Pakruddin B[2], Deepa Yogish[3]
[1]Department of Computer Science and Engineering, M S Ramaiah Institute of Technology, Bengaluru, Visvesvaraya Technology University, Belagavi, India
[2]Department of Computer Science and Engineering, Presidency University, Bengaluru, India
[3]Department of Computer Science and Engineering, Christ University, Bengaluru, India

Article Info

Article history:

Received May 22, 2025
Revised Jul 21, 2025
Accepted Sep 14, 2025

Keywords:

Agriculture
Deep learning
Feature extraction
Image processing
Pretrained models
Soil type prediction

ABSTRACT

Agriculture is the backbone of the Indian economy, with soil quality playing a crucial role in crop productivity. Farmers often struggle to select the appropriate crop based on soil type, leading to significant losses in yield and productivity. To address this challenge, deep learning techniques provide an efficient solution for automated soil classification. In this study, a dataset of 781 original soil images, including clay soil, alluvial soil, red soil, and black soil, was collected from Kaggle and augmented to 3,702 images to enhance model training. Several deep learning models were employed for soil classification, including pretrained architectures and a proposed model, SoilNet. Experimental results demonstrated that DenseNet201 achieved 100% validation accuracy, ResNet50V2 98%, VGG16 99%, MobileNetV2 99%, and the proposed SoilNet model 97%. The proposed approach outperformed existing work by surpassing 95% accuracy. Additionally, model performance was evaluated using precision, recall, and F1-score, ensuring a comprehensive analysis of classification effectiveness. These findings highlight the potential of deep learning in improving soil classification accuracy, aiding farmers in making informed crop selection decisions.

Corresponding Author:

Praveen Pawaskar
Department of Computer Science and Engineering, M S Ramaiah Institute of Technology, Bengaluru, Visvesvaraya Technological University
Belagavi – 590018, India
Department of Computer Science and Engineering, Presidency University
Bengaluru – 560064, India
Email: praveenpawaskar555@gmail.com

1. INTRODUCTION

The foundation of worldwide food production is agriculture, and crop yield is heavily influenced by the quality of the soil. Soil types—like sandy, clayey, loamy, and silt—differ in texture, water retention capacity, and nutrient availability, which directly affects plant growth. Farmers need to understand soil properties in order to make informed choices about crop selection, irrigation, and fertilization. Nonetheless, conventional methods of soil analysis are frequently characterized by high costs and time demands, as well as a lack of accessibility for numerous farmers—especially those in isolated regions. The progress made in artificial intelligence (AI) and deep learning has sparked increased curiosity about using technology to enhance agricultural practices [1].

A significant challenge for contemporary agriculture is that fluctuations in soil and environmental conditions can lead to unpredictable crop performance. Farmers frequently depend on traditional methods or manual testing to evaluate soil suitability, which can result in inefficient resource allocation and reduced productivity [2]. Furthermore, the decision-making process is made more complex by climate change and soil degradation, which hinders the attainment of sustainable farming that also yields high production. Pre-trained deep learning models like VGG and ResNet have proven effective in image classification and pattern recognition, but their direct use in agriculture necessitates fine-tuning to suit specific soil and crop conditions [3].

This study aims to meet these challenges by focusing on the fine-tuning of pre-trained deep learning models for the purpose of accurate crop prediction based on soil conditions [4]. These models can evaluate soil texture, moisture levels, and nutrient content to suggest the most appropriate crops for a specific area by using soil images and related data. AI-driven smart agriculture solutions can greatly improve decision-making, minimize trial-and-error farming methods, and boost overall yield. This research seeks to connect the fields of deep learning and precision agriculture, offering farmers a trustworthy, data-informed method for optimizing productivity and sustainability. This research improves precision farming through the use of DenseNet121 and ResNet50 for accurate crop classification from satellite images, facilitating improved decision-making and resource management.

Section 2 outlines related work, Section 3 outlines the proposed methodology, including data acquisition, preprocessing, model fine-tuning, and evaluation. Section 4 discusses the experimental setup, results, and analysis. Section 5 concludes the study with key findings, limitations, and directions for future work.

2. RELATED WORK

Jasvanth and Fredrik [5] proposed a convolutional neural network (CNN)-based method for classifying soil images and recommending crops, thereby improving precision agriculture. Using preprocessing techniques to standardize input data, the model is trained on analyses dataset of different soil types [6]. Following classification, the system recommends appropriate crops, offering an automated and effective means for making informed agricultural decisions. The purpose of research [7] is to help farmers choose appropriate crops by examining the characteristics of land and soil through geospatial methods. To assess the appropriateness of crops, elements such as soil texture and moisture levels, nutrient content, and slope are analyses. A web-based model that processes dynamic data facilitates improved planning and enhances the yield per hectare.

Reference [8] puts forward a supervised learning model based on decision trees to improve the accuracy of crop yield predictions using soil moisture parameters and to decrease error rates. It examines current machine learning (ML) algorithms, elaborates on the proposed approach, evaluates outcomes, and considers potential enhancements, providing useful perspectives for researchers in agricultural artificial intelligence (AI). Using deep learning, authors proposed CNN-based method analyses soil characteristics [9] and forecasts appropriate crops, guaranteeing a solution rooted in data. Through comprehensive testing on actual datasets, high accuracy and efficiency have been shown, promoting precision agriculture for improved soil classification and crop forecasting [4]. Ahmed *et al.* [10] utilizes machine learning to forecast significant cropping patterns in Bangladesh, drawing on land, soil, and climate data from 52 Upazilas. Models such as k-nearest neighbors (KNN), decision tree (DT), random forest classifier (RFC), extreme gradient boosting (XGBoost), and support vector machine (SVM) are capable of managing mixed data and various crop classes with an accuracy exceeding 95%. Additionally, a system that is easy to use was created for straightforward prediction deployment. Mittal and Bhanja [11] developed an ML model that recommends optimal crops based on soil, climate, and resources. Using natural language processing (NLP) to extract insights from crop data, the model predicts suitable crops and is deployed as a web service for easy access.

Alluvial soil, located in river plains such as those of the Ganges, Brahmaputra, and Indus, is extremely fertile and mineral-rich, making it perfect for farming. It is conducive to the farming of staple crops like rice, wheat, sugarcane, pulses, and oilseeds due to its excellent drainage and moisture retention capabilities. Due to its nutrient-rich composition, it ensures high yields and is among the most productive soil types for farming [12]. Also referred to as regur soil, black soil is very fertile and ideal for growing cotton, soybean, sunflower, maize, and pulses. It is mainly located in Maharashtra, Gujarat, and Madhya Pradesh, and it retains moisture well, making it suitable for dryland agriculture. Black soil, which is abundant in calcium and magnesium, promotes nutrient uptake and guarantees robust crop growth. Its ability to self-plow diminishes the necessity for regular tilling, thus boosting agricultural productivity [13]. Red soil, located in areas such as Tamil Nadu, Karnataka, and Odisha, has good drainage and is high in iron content. However, its natural fertility is low, necessitating the use of fertilizers for ideal crop development. It is appropriate for the cultivation of groundnut, millets, pulses, cotton, rice, and various vegetables. With appropriate soil management and fertilization, red soil can sustain agriculture and improve crop yield [14].

Water-intensive crops like paddy, wheat, barley, and vegetables thrive in clayey soil that is nutrient-rich and retains moisture effectively. This soil type, mainly located in areas such as Assam and West Bengal, facilitates high-yield agriculture but necessitates effective drainage management to avert waterlogging. Due to its fertile characteristics, it is ideal for sustainable crop production when proper irrigation methods are applied and soil aeration is sufficient [15].

Groundnut is a vital food and oilseed crop in West Africa, contributing significantly to food and nutritional security. This study aimed to assess the impact of different soil types on the nutritional quality of groundnut in Lebda village, Centre-North Burkina Faso. Groundnut seeds (SH 470 P variety) were collected from fourteen farmers across three soil types, and their macronutrient and mineral contents were analyzed. Variance analysis revealed significant differences: clay soils yielded seeds with higher fat content (46.6% ± 6.3 g/100 g dry matter), while gravelly soils produced seeds richer in carbohydrates (18.8 ± 1.9 g/100 g dry matter). Iron content ranged from 1.9 ± 0.5 mg/100 g on sandy soils to 2.46 ± 0.39 mg/100 g on clay soils [16], [17]. A two-year field study at Himachal Pradesh Agricultural University, Palampur, assessed the impact of vermicompost and split-applied nitrogen on pole French bean. Twelve treatment combinations were tested, varying organic manures, nitrogen levels, and application methods. The combination of vermicompost with 125% recommended nitrogen applied in splits achieved the highest seed yield of 10.43 q/ha and improved nutrient uptake. Vermicompost with 75% nitrogen also matched full-dose yields, enabling a 25% fertilizer saving. Split application at 125% nitrogen increased yields by 50% over basal application, highlighting that integrating vermicompost with split nitrogen application boosts productivity and supports soil health [18].

Field experiments were conducted during the summer, kharif, and rabi seasons of 2016–2017 and 2017–2018 at AC & RI, TNAU, Madurai to assess the impact of nutrient management and soil amendments on groundnut productivity. The study tested three irrigation levels (I1: 0.8 IW/CPE, I2: 0.6 IW/CPE, I3: 0.6 IW/CPE) and four nutrient management practices (N1–N4) involving varying fertilizer rates, charred rice husk, and Arbuscular mycorrhizae seed treatments. Results revealed that applying 75% of the recommended fertilizer along with 5t of charred rice husk and Arbuscular mycorrhizae significantly enhanced plant growth, dry matter production, leaf area index, SPAD value, nutrient uptake, soil enzyme activity, and yields. The highest pod yields (1783, 1935, and 1854 kg/ha) and haulm yields (4743, 4272, and 4338 kg/ha) were achieved during summer, kharif, and rabi 2017, respectively, under this treatment [19]. A 10-year study on organic, integrated, and inorganic nutrient management systems assessed their impact on soil microbiological properties. Results showed a C mineralization rate of 6.8 mg/kg soil and a potentially mineralizable nitrogen level of 41.5 mg/kg soil. Arginine ammonification and nitrification activities measured 0.88 µg NH_4^+-N/g soil/h and 56.0 µg NO_3^--N/g/day, respectively. Microbial biomass C, N, and P were 320, 40, and 12 mg/kg soil. The highest activities of alkaline phosphatase, urease, and cellulase were observed with vermicompost application at 15 t/ha [20].

According to Ghani *et al.* [21], when it comes to forecasting soil liquefaction, long short-term memory network (LSTM) outperforms CNN, XGB, and CatB. Its accuracy is 0.96, and its F1-score is 0.95. Additionally, it shows that the soil with the largest liquefaction risk is SM-SP, providing important information for geotechnical engineers.

3. THE PROPOSED METHOD

3.1. Dataset used

We have collected dataset from Kaggle, which includes 3,702 enhanced photographs in addition to 781 original dirt photos as shown in Figure 1. Twenty percent of the data is used for testing during training, and eighty percent is used for training. Four soil groups are represented in the dataset: clay soil (995 photos), red soil (910 images), black soil (985 images), and alluvial soil (812 images).

3.2. Pre-processing and data augmentation

The preparatory stages in the code include fetching photos from subfolders, using cv2.resize () to resize them to 224×224 pixels, and using $LabelEncoder$ () to encode class labels before one-hot encoding with $to\_categorical$ (). To increase training stability, images are normalized by scaling pixel values to the [0, 1] range. To ensure correct model evaluation, $train\_test\_split$ () divides the dataset into 80% training and 20% validation. A dropout layer (0.5 probability) is incorporated to avoid overfitting. Although flipping and rotation are not used explicitly, $ImageDataGenerator$ () can be used to incorporate them.

3.3. Performance metrics

The accuracy, precision, recall, F1-score, and support metrics are used to assess the performance of deep learning models. While the confusion matrix true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) aid in evaluating the efficacy of classification, support shows the distribution of classes [22].

Figure 1. Sample images from dataset

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1 - score = \frac{2\ X\ Precision\ X\ Recall}{Precision+Recall} \quad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

3.4. Proposed model architecture

A structured deep learning pipeline is used by the suggested soil categorization model as shown in Figure 2. To improve model performance, it starts with an input dataset of soil images that is pre-processed and enhanced. After that, the dataset is divided into 20% testing and 80% training. Using accuracy, precision, recall, and F1-score, several deep learning models—SoilNet, VGG16, ResNet50V2, DenseNet201, and MobileNetV2—are trained and assessed. Alluvial soil, black soil, clay soil, and red soil are distinguished by the categorization system. In order to maximize model performance and guarantee accurate and reliable soil categorization, hyper parameter adjustment is included [23].

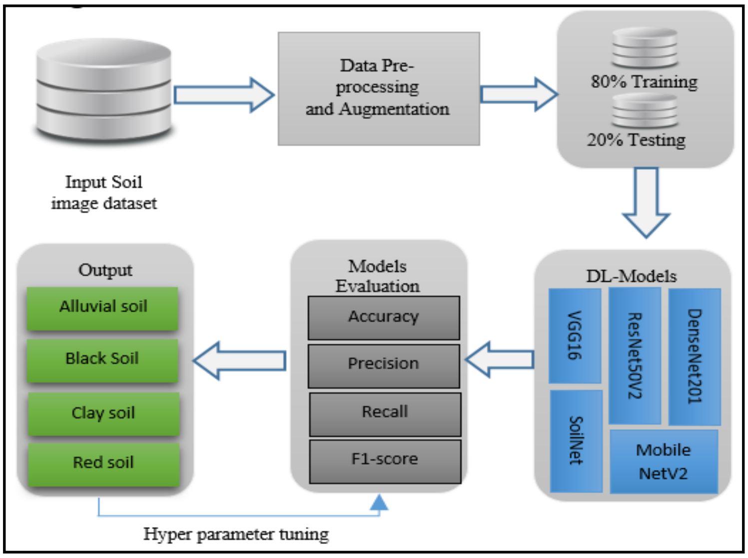

Figure 2. Proposed model architecture

3.5. Feature extraction by SoilNet CNN model

The following is a mathematical representation of the feature extraction procedure for the suggested SoilNet model:

a. Convolutional layer operations

$$F_l = \sigma (W_l * X_{l-1} + b_l) \tag{5}$$

where F_l is the feature map at layer l, W_l and b_l are the learned filters and biases, X_{l-1} is the input from the previous layer, $*$ denotes the convolution operation, σ is the activation function (ReLU).

b. Max-pooling for down sampling

$$P_l = \max (F_l) \tag{6}$$

P_l represents the pooled feature map, max () denotes max pooling with a 2×2 filter.

c. Flattening and fully connected layers

$$Z=\text{Flatten} (P_l) \tag{7}$$

$$H=\sigma (W_{fc} \cdot Z + b_{fc}) \tag{8}$$

Where Z is the flattened vector, H is the output of the dense layer, W_{fc} and b_{fc} are the weight matrix and bias of the dense layer.

d. SoftMax classification

$$\widehat{y_i} = \frac{e^{z_j}}{\sum_{j=1}^{N} e^{z_j}} \tag{9}$$

$\widehat{y_i}$ is the probability of class i, N is the total number of classes **(**4 soil types**)**, Z_i is the activation output for class i. Together, these procedures make up the SoilNet models feature extraction pipeline, which allows it to identify patterns in soil texture for categorization.

4. EXPERIMENTAL RESULTS

The code for all experiments was implemented and executed in Google Colab, using the most recent versions of Keras and TensorFlow. Table 1 provides a detailed account of the hardware specifications used during the trials [24].

Table 1. Hardware requirements for experiments

Hardware component	Specification
GPU	Tesla T4, High RAM
System RAM	50.99 GB
Disk storage	238.68 GB

Trained models' performance without data augmentation for soil classification is summarized in Table 2. The highest accuracy (92%) was achieved by DenseNet201, with F1-scores ranging from 0.91 to 0.93. At 91%, ResNet50V2 came in second place, demonstrating exceptional performance in Black Soil (F1-score: 0.95). Both VGG16 and MobileNetV2 achieved 90%, with MobileNetV2 demonstrating a high precision of 0.96 for Alluvial Soil. While the SoilNet model reached an accuracy of 83%, it excelled in Red Soil (F1-score: 0.99) but had difficulties in Clay Soil (F1-score: 0.67), highlighting the need for enhancements.

As per the performance assessment of trained models with augmentation as shown in Table 3, DenseNet201 reached the highest accuracy (100%), followed by VGG16 and MobileNetV2 (99%) and ResNet50V2 (98%). The proposed SoilNet model achieved an accuracy of 97%, demonstrating superior performance in classifying black and clay soils. Although DenseNet201 showed the best classification results, all models exhibited competitiveness with slight differences in metrics.

The proposed models' accuracy, loss, and computational performance were examined both with and without augmentation in Tables 4 and 5. Without augmentation, DenseNet201 and ResNet50V2 attained a flawless training accuracy of 100%, yet their testing accuracies fell to 91.81% and 90.64%, respectively. The training accuracy of VGG16 and MobileNetV2 was somewhat lower, at 92.81% and 100%, respectively, while the testing accuracy hovered around 90%. The proposed SoilNet model demonstrated a training accuracy of 95.98%, but it had the lowest testing accuracy (83.83%) and higher testing loss. DenseNet201 achieved a 100% testing accuracy and minimal loss (0.0032) with augmentation, outperforming all models. With accuracies of 99.46% and 98.79%, VGG16 and MobileNetV2 were not far behind. With accuracies of 97.98% and 97.57%, respectively, ResNet50V2 and the proposed SoilNet model exhibited enhanced generalization in comparison to training without augmentation. Overall, augmentation considerably improved model performance, lessening overfitting and increasing testing accuracy.

Table 2. Performance evaluation of trained models without augmentation

Models	Classes	Precision	Recall	F1-score	Accuracy
DenseNet201	Alluvial soil	0.94	0.88	0.91	92%
	Black Soil	0.88	0.95	0.91	
	Clay soil	0.95	0.90	0.93	
	Red soil	0.92	0.94	0.93	
ResNet50V2	Alluvial soil	0.91	0.84	0.88	91%
	Black Soil	0.91	0.98	0.95	
	Clay soil	0.86	0.86	0.86	
	Red soil	0.93	0.94	0.93	
VGG16	Alluvial soil	0.93	0.86	0.89	90%
	Black Soil	0.91	0.95	0.93	
	Clay soil	0.90	0.86	0.88	
	Red soil	0.86	0.92	0.89	
MoileNetV2	Alluvial soil	0.96	0.83	0.89	90%
	Black Soil	0.89	0.95	0.92	
	Clay soil	0.86	0.90	0.88	
	Red soil	0.87	0.94	0.90	
Proposed SoilNet Model	Alluvial soil	0.83	0.70	0.76	83%
	Black Soil	0.97	0.71	0.82	
	Clay soil	0.51	0.95	0.67	
	Red soil	0.98	1.00	0.99	

Table 3. Performance evaluation of trained models with augmentation

Models	Classes	Precision	Recall	F1-score	Accuracy
DenseNet201	Alluvial soil	1.00	1.00	1.00	100%
	Black Soil	1.00	1.00	1.00	
	Clay soil	1.00	1.00	1.00	
	Red soil	1.00	1.00	1.00	
ResNet50V2	Alluvial soil	1.00	0.97	0.99	98%
	Black Soil	0.96	0.99	0.97	
	Clay soil	0.96	0.96	0.96	
	Red soil	1.00	1.00	1.00	
VGG16	Alluvial soil	1.00	0.98	0.99	99%
	Black Soil	1.00	1.00	1.00	
	Clay soil	0.99	0.99	0.99	
	Red soil	0.99	1.00	0.99	
MoileNetV2	Alluvial soil	0.99	0.99	0.99	99%
	Black Soil	0.98	0.98	0.98	
	Clay soil	0.98	0.98	0.98	
	Red soil	1.00	1.00	1.00	
Proposed SoilNet Model	Alluvial soil	0.93	0.99	0.96	97%
	Black Soil	1.00	0.97	0.98	
	Clay soil	0.97	1.00	0.98	
	Red soil	0.99	0.92	0.95	

Table 4. Accuracy, Loss and time computing of proposed models without augmentation

Pre-Trained model	Training Accuracy (%)	Training Loss (%)	Testing Accuracy (%)	Testing Loss (%)
DenseNet201	100	0.0051	91.81	0.2139
ResNet50V2	100	0.0091	90.64	0.3241
VGG16	92.81	0.2429	90.06	0.2926
MoileNetV2	100	0.0050	90.06	0.3106
Proposed SoilNet Model	95.98	0.0970	83.83	0.5016

Table 5. Accuracy, loss and time computing of proposed models with augmentation

Pre-Trained model	Training Accuracy (%)	Training Loss (%)	Testing Accuracy (%)	Testing Loss (%)
DenseNet201	99.98	0.0012	100	0.0032
ResNet50V2	99.93	0.0020	97.98	0.0540
VGG16	99.78	0.0129	99.46	0.0179
MoileNetV2	100	0.0035	98.79	0.0224
Proposed SoilNet Model	99.55	0.0126	97.57	0.1982

All models' training and validation accuracy/loss curves show a consistent rise in accuracy over epochs as loss decreases. SoilNet's exceptional performance in soil classification is confirmed by its near-perfect accuracy. High accuracy is also demonstrated by ResNet50V2, VGG16, DenseNet201, and MobileNetV2, with slight variations in validation loss suggesting some volatility but overall good generalization. All models operate well, but SoilNet is the most dependable for soil categorization since it performs better than the others in terms of accuracy and stability. Figure 3 shows training, testing accuracy and loss curves.

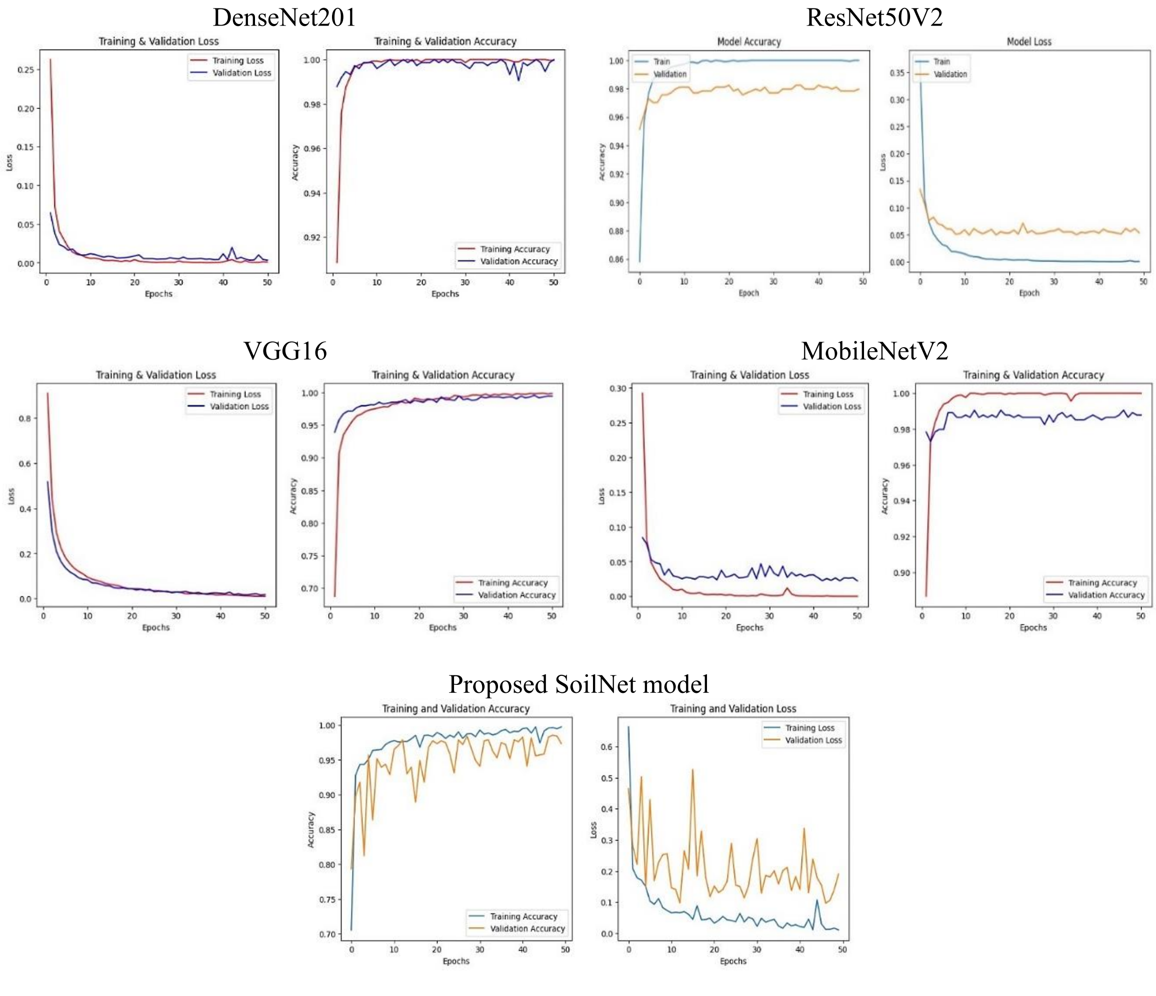

Figure 3. Training and testing accuracy and loss analysis

In soil classification, the confusion matrices of different models show how effective they are. DenseNet201's robustness is demonstrated by its perfect classification with zero misclassifications across all four soil types (Alluvial, Black, Clay, and Red). High accuracy is demonstrated by ResNet50V2, which classifies the majority of samples accurately with few errors. It primarily confuses clay soil with black soil and alluvial soil with other categories. With a few small misclassifications in clay and alluvial soil but excellent overall accuracy, VGG16 performs admirably as well. With very few incorrect classifications including Clay and Black Soil, MobileNetV2 continues to exhibit strong classification performance. Although 13 Red Soil samples were incorrectly classified as Alluvial Soil, the suggested SoilNet model shows remarkable accuracy, especially in Alluvial, Black, and Clay soils. Nevertheless, SoilNet performs better than other models, making it a very useful soil classification as shown in Figure 4.

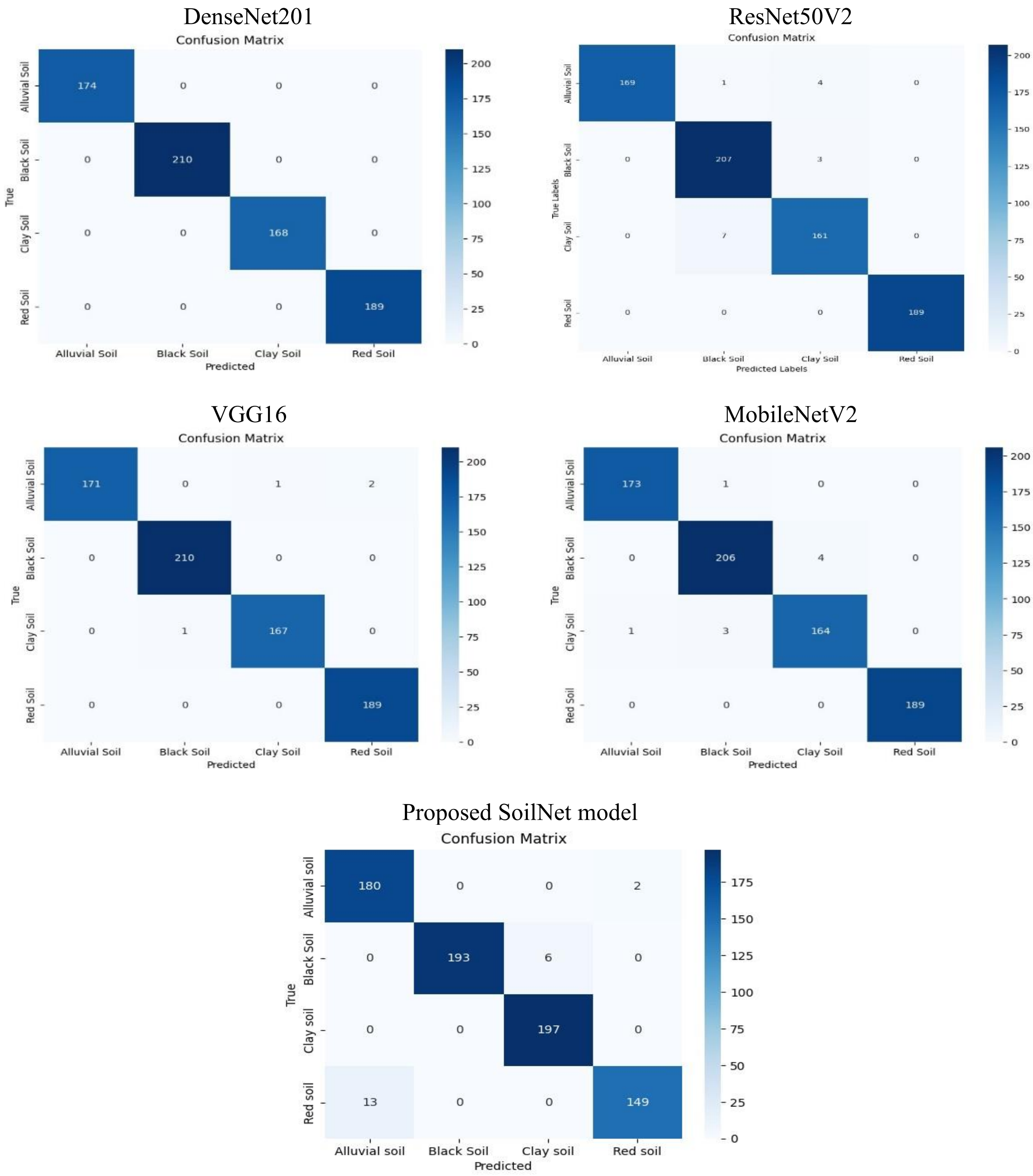

Figure 4. Confusion matrix of proposed models

By graphing the true positive rate (TPR) versus the false positive rate (FPR), the ROC curves assess deep learning models for multi-class soil classification and demonstrate their capacity for discrimination. The area under the curve (AUC) is used to evaluate models such as SoilNet, ResNet50V2, VGG16, DenseNet201, and MobileNetV2. Values near 1.0 indicate good classification performance. Robust generalization is confirmed by higher AUC across all soil classes; SoilNet most likely achieves the greatest AUC, demonstrating its improved accuracy. ROC curve comparison aids in identifying the best accurate model for soil classification as shown in Figure 5. Table 6 proposed model comparison with other studies.

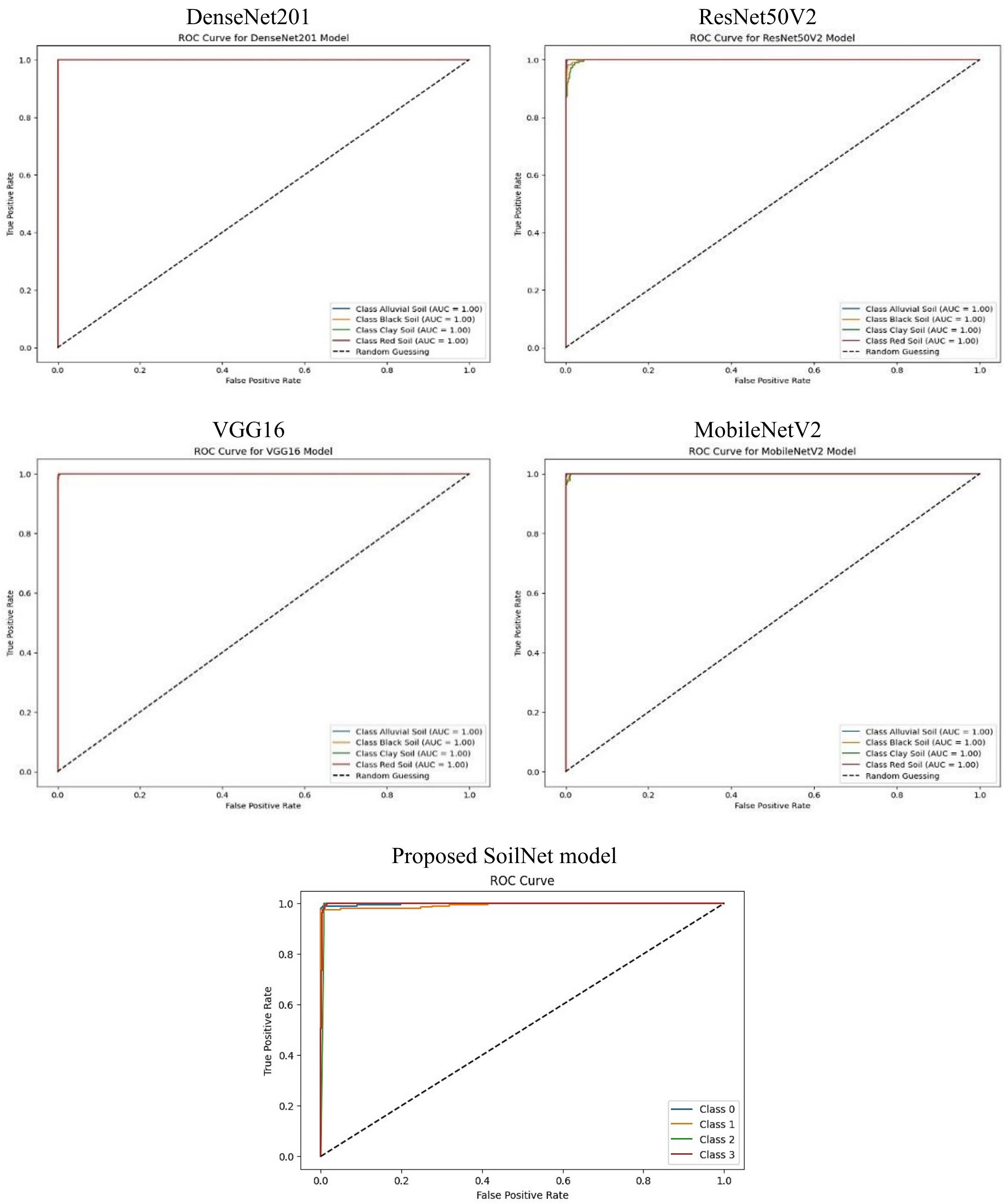

Figure 5. ROC curves of proposed models

Table 6. Proposed model comparison with other studies

References	Year	Dataset used	Accuracy (%)
Proposed work	2025	Kaggle	97%
[10]	2022	Kaggle	95%

5. CONCLUSION

In order to facilitate informed crop selection in precision agriculture, this paper offers a thorough assessment of deep learning methods for soil categorization. The performance of four popular pre-trained models—DenseNet201, ResNet50V2, VGG16, and MobileNetV2—was compared to the suggested SoilNet CNN model using a carefully selected dataset of 3,702 soil pictures (original and enhanced). These demonstrated the robustness of deep learning in soil-type prediction, with DenseNet201 achieving the greatest classification accuracy (100%), followed by VGG16 and MobileNetV2 (99%), ResNet50V2 (98%), and the suggested SoilNet (97%). Our models, especially DenseNet201, showed better generalization and classification precision than previous studies that indicated a maximum of 95% accuracy, especially after adding data augmentation. Notably, the SoilNet model demonstrated exceptional class-specific precision, especially for red and clay soils, highlighting its potential in specialized classification tasks, although marginally lagging behind in aggregate performance. This study has significant ramifications for smart agriculture since it can replace labor-intensive manual soil testing with automated soil classification based on image data, allowing for location-aware crop suggestions in real time. Our results highlight how important it is to incorporate deep learning into agricultural systems in order to achieve high-yield, sustainable farming. We intend to build on this research in the future by adding multimodal soil characteristics (such as pH, moisture, and nutrient content), refining models for mobile real-time applications, and confirming results on soil samples at the field level. These developments will improve the use of AI-powered precision agriculture instruments in a variety of environmental settings.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Praveen Pawaskar	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Yogish H K		✓				✓		✓		✓		✓		
Pakruddin B	✓		✓	✓			✓				✓		✓	✓
Deepa Yogish				✓			✓				✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle [25].

REFERENCES

[1] J. P. Sarvaiya, A. P. Chaudhari, and J. P. Verma, “Monitoring agricultural essentials,” in *Application of Machine Learning in Agriculture*, Elsevier, 2022, pp. 29–46. doi: 10.1016/B978-0-323-90550-3.00004-7.

[2] V. Kakani, V. H. Nguyen, B. P. Kumar, H. Kim, and V. R. Pasupuleti, “A critical review on computer vision and artificial intelligence in food industry,” *Journal of Agriculture and Food Research*, vol. 2, p. 100033, Dec. 2020, doi: 10.1016/j.jafr.2020.100033.

[3] M. Peng *et al.*, “Crop monitoring using remote sensing land use and land change data: Comparative analysis of deep learning methods using pre-trained CNN models,” *Big Data Research*, vol. 36, p. 100448, May 2024, doi: 10.1016/j.bdr.2024.100448.

[4] G. R. Sri and A. Vikram, “Soil type detection and crop prediction using deep learning method CNN,” in *2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC)*, Jul. 2024, pp. 1090–1094. doi: 10.1109/AIC61668.2024.10730858.

[5] S. M. Jasvanth and E. J. T. Fredrik, “Soil image classification and crop recommendation using convolutional neural networks,” in *2024 2nd International Conference on Computing and Data Analytics (ICCDA)*, Nov. 2024, pp. 1–6, doi: 10.1109/ICCDA64887.2024.10867325.

[6] D. N. Kiran Pandiri, R. Murugan, and T. Goel, “Smart soil image classification system using lightweight convolutional neural network,” *Expert Systems with Applications*, vol. 238, p. 122185, Mar. 2024, doi: 10.1016/j.eswa.2023.122185.

[7] S. Patel, N. Shinolikar, V. Patkar, and T. P. Singh, "Spatial decision support system for impact analysis of soil characteristics on crop production using geo-spatial technologies," in *2021 IEEE 2nd International Conference on Technology, Engineering, Management for Societal impact using Marketing, Entrepreneurship and Talent (TEMSMET)*, Dec. 2021, pp. 1–7. doi: 10.1109/TEMSMET53515.2021.9768754.

[8] S. M. G, S. Paudel, R. Nakarmi, P. Giri, and S. B. Karki, "Prediction of crop yield based-on soil moisture using machine learning algorithms," in *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, Oct. 2022, pp. 491–495. doi: 10.1109/ICTACS56270.2022.9988186.

[9] M. Kim, M. A. Senturk, R. K. Tan, E. Ordu, and J. Ko, "Deep learning approach on prediction of soil consolidation characteristics," *Buildings*, vol. 14, no. 2, p. 450, Feb. 2024, doi: 10.3390/buildings14020450.

[10] S. Ahmed, S. Yesmin, L. R. Saha, A. K. M. Sadat, and M. H. A. Khan, "Major cropping pattern prediction in Bangladesh from land, soil and climate data using machine learning techniques," in *2022 25th International Conference on Computer and Information Technology (ICCIT)*, Dec. 2022, pp. 988–993. doi: 10.1109/ICCIT57492.2022.10056051.

[11] N. Mittal and A. Bhanja, "Implementation and identification of crop based on soil texture using AI," in *2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Jul. 2023, pp. 1467–1471. doi: 10.1109/ICESC57686.2023.10192937.

[12] A. Das *et al.*, "Various organic nutrient sources in combinations with inorganic fertilizers influence the yield and quality of sweet corn (Zea mays L. saccharata) in new alluvial soils of West Bengal, India," *Phyton*, vol. 93, no. 4, pp. 763–776, 2024, doi: 10.32604/phyton.2024.049473.

[13] K. Velmourougane *et al.*, "Soil dehydrogenase activity in agro-ecological sub regions of black soil regions in India," *Geoderma*, vol. 197–198, pp. 186–192, Apr. 2013, doi: 10.1016/j.geoderma.2013.01.011.

[14] I. Rashmi, A. K. Biswas, K. S. Kartika, and S. Kala, "Phosphorus leaching through column study to evaluate P movement and vertical distribution in black, red and alluvial soils of India," *Journal of the Saudi Society of Agricultural Sciences*, vol. 19, no. 3, pp. 241–248, Apr. 2020, doi: 10.1016/j.jssas.2018.11.002.

[15] S. Duhan *et al.*, "Suitability of clayey soils from Jalore and Jodhpur, Rajasthan, India for the production of 3-Litre ceramic water filters," *Desalination and Water Treatment*, vol. 309, pp. 210–219, Oct. 2023, doi: 10.5004/dwt.2023.29873.

[16] H.-B. Fatoumata, K. Roland, K. Roger, and M. H. Dicko, "Effect of soil type on the nutritional quality of groundnut (Arachis hypogaea L) in Burkina Faso," *Legume Research-An International Journal*, vol. 45, no. 12, pp. 1568–1571, 2022.

[17] M. M. Shoaib and M. Y. Abu-Farsakh, "Developing tree-based machine learning models for estimating the pile setup parameter for clay soils," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2679, no. 1, pp. 656–669, Jan. 2025, doi: 10.1177/03611981241236180.

[18] A. Sharma, R. P. Sharma, V. Katoch, and G. D. Sharma, "Influence of vermicompost and split applied nitrogen on growth, yield, nutrient uptake and soil fertility in pole type frenchbean (Phaseolus vulgaris L.) in an Acid Alfisol," *LEGUME RESEARCH - AN INTERNATIONAL JOURNAL*, vol. 41, no. OF, pp. 126–131, Aug. 2017, doi: 10.18805/lr.v0iOF.9107.

[19] P. Balasubramanian, R. Babu, C. R. Chinnamuthu, P. P. Mahendran, and K. Kumutha, "Soil application of different nutrient levels with soil amendment charred rice husk and seed treatment of arbuscular mycorrhizae: effects on crop productivity and nutrient uptake on groundnut (Arachis hypogaea L.)," *LEGUME RESEARCH - AN INTERNATIONAL JOURNAL*, vol. 47, no. Of, pp. 1543–1548, Oct. 2021, doi: 10.18805/LR-4727.

[20] N. Nisha, M. Walia, N. Batra, R. Gera, and S. Goyal, "Impact of management practices on soil microbial properties under wheat-cluster bean cropping system," *LEGUME RESEARCH - AN INTERNATIONAL JOURNAL*, vol. 42, no. of, pp. 565–571, Jan. 2018, doi: 10.18805/LR-3908.

[21] S. Ghani, I. Thapa, D. K. Adhikari, and K. A. Waris, "Soil categorization and liquefaction prediction using deep learning and ensemble learning algorithms," *Transportation Infrastructure Geotechnology*, vol. 12, no. 1, p. 22, Jan. 2025, doi: 10.1007/s40515-024-00474-8.

[22] B. Pakruddin and R. Hemavathy, "Performance analysis of various deep transfer learning models for bacterial blight disease detection and classification in pomegranate fruits," *Indian Journal of Agricultural Research*, vol. 59, no. 6, pp. 979–987, 2025, doi: 10.18805/IJARe.A-6245.

[23] B. Pakruddin and R. Hemavathy, "Detection of fusarium wilt disease in pomegranate plants using deep learning techniques," in *IEEE International Conference on Modeling, Simulation and Intelligent Computing, MoSICom 2024 - Proceedings*, 2024, pp. 212–217. doi: 10.1109/MoSICom63082.2024.10881292.

[24] M. R. Barman, A. A. Biswas, M. Sultana, A. Rajbongshi, M. S. Zulfiker, and T. Tabassum, "Automated classification of diseased cauliflower: a feature-driven machine learning approach," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 22, no. 4, pp. 887–896, 2024, doi: 10.12928/TELKOMNIKA.v22i4.25812.

[25] Jayaprakashpondy, "Soil image dataset," *Kaggle*. [Online]. Available: https://www.kaggle.com/datasets/jayaprakashpondy/soil-image-dataset

BIOGRAPHIES OF AUTHORS

Praveen Pawasakr received his B.E. and M.Tech degrees in Computer Science and Engineering, and is currently pursuing a Ph.D. in Computer Science and Engineering from Visvesvaraya Technological University (VTU), Belagavi – 590018. He is presently serving as an Assistant Professor in the School of Computer Science and Engineering & Information Science at Presidency University, Bengaluru – 560064. With over 20 years of teaching experience and 2 years in IT his research interests span web technology, embedded systems, computer organization, deep learning and machine learning. He can be contacted via email at: praveenpawaskar555@gmail.com.

Yogish H K is a professor in the Department of Information Science and Engineering with over 25 years of teaching experience. He holds a B.E. in Computer Science, M.Tech. in Computer Engineering, Ph.D. in Computer Science, and a PG Diploma in Cyber Law and Forensics from NLSIU, Bengaluru. He has successfully guided five Ph.D. scholars and is currently mentoring six molre under VTU. Dr. Yogish has published 103 papers, including 25 indexed in Scopus/Web of Science, 16 in IEEE, and three in DBLP. He has authored three textbooks, contributed to five book chapters, holds two patents and one copyright, and secured funding from AICTE and DST. A frequent keynote speaker and reviewer, he is associated with FIE, ISTE, CSI, and IAENG. His research interests include knowledge representation, data mining, cloud computing, and IoT. He can be contacted via email at: yogishhk@gmail.com.

Pakruddin B received his B.E. and M.Tech degrees in Computer Science and Engineering, and is currently pursuing a Ph.D. in Computer Science and Engineering from Visvesvaraya Technological University (VTU), Belagavi – 590018. He is presently serving as an Assistant Professor in the School of Computer Science and Engineering & Information Science at Presidency University, Bengaluru – 560064. With over 16 years of teaching experience, his research interests span deep learning, machine learning, and image processing. He has published more than 10 research papers in Scopus-indexed international journals and over 10 papers in Scopus-indexed international conferences. He can be contacted via email at: fakrubasha@gmail.com.

Deepa Yogish is working as associate professor in the Department of Computer Science & Engineering. Completed B. E from VTU Belagavi, M.Tech in Computer Science Engineering from VTU Belagavi and Ph.D. in Computer Science from VTU Belagavi. She has published and presented 17 papers at National/International Conferences/Journals among SEVEN papers were indexed by Scopus, and one BOOK Chapter. She has an extensive experience of 17+ years of Teaching Experience and worked in various capacities from Lecturer to associate professor. She is a life time member of various professional bodies – IE, LMISTE and IAENG. She is the proud owner of various awards in the fields of Teaching and Coordination. She can be contacted at email: deepa.yogish@christuniversity.in.