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Original Article

SoilClass: A Novel Image Dataset For Soil Classification

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ABSTRACT

Soil classification is one of the most important topics in the field of agricultural development. It has significant importance in agricultural, environmental science, and geotechnical engineering. It assists in soil preparation, choosing of crops, checking moisture levels and automation. Traditional and analytical methods of soil categorization are laborious, costly, and demanding a high degree of competence. This study describes a quick and cost-effective method for predicting soil types using soil images. To create the soil image dataset, a total of five types of soil samples were collected from different parts of West Bengal. Later, the collected samples are tested with the help of the soil testing laboratory, West Midnapore, West Bengal, India. Later, we created an imaging setup and captured a total of 552 images of these five categories of soils from different angles and various light conditions. We used five convolutional neural networks (CNNs) models, namely, MobileNetV2, InceptionV3, ResNet152, ResNet50, and DenseNet201 for the soil classification task. In our dataset, DenseNet201 and InceptionV3 achieved the highest accuracy, and ResNet50 achieved the lowest accuracy.

1. Introduction

In recent decades, population growth has led to reduced land available for agriculture. With the rising population, there is a need to increase food grain production on available land. Soil classification plays a vital role in helping farmers achieve proper and profitable cropping on available agricultural land. Conventional soil categorization procedures are frequently time-intensive and laborious because they are based on manual

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collection and analysis. This study tries to introduce an example in soil classification by harnessing the capabilities of CNNs, a branch of deep learning (DL), using a few classes for the classification of soil types that are well-suited for image analysis tasks. The significance of this dataset lies in its ability to bridge the gap between traditional soil classification methods and the demands of modern, data-driven approaches.

The main contributions of this paper are as follows:

- Collecting the soil samples from various locations in West Bengal and testing those soils in the Soil Testing Laboratory, Midnapore.
- Capturing their mages using various mobile. Due to using various mobile cameras, we got various dimensions of the images.
- After completing those steps, we got an image dataset that was divided into three parts: train data, test data, and validation data. Each part contains a total of five classes.
- After getting the dataset, we trained those datasets using various CNN models, and we got various results, which will be discussed in this section.

2. Related Work

In this section, we provide an overview of several soil classification methods using DL techniques. Here we provide the details of the literature survey that we studied for our research purposes. The details of each paper are given below:

Hamzah et al. [1] created their own dataset and used Multilayer Perceptron (MLP) to train the dataset with Adam, RMSprop, and SGD optimizers. By using these optimizers, they got 0.9800, 0.9276, and 0.6479 as training accuracies, with training losses of 0.1877, 0.3040, and 0.6784 respectively, while 0.9784, 0.9139, and 0.5268 are the testing accuracies, with testing losses of 0.0815, 0.2699, and 0.6905 respectively. Girme et al. [2] developed two datasets, such as the soil dataset and crop dataset, and trained CNN, Support Vector Machine (SVM), and k-nearest neighbor (k-NN) techniques. This paper discusses the importance of soil health analysis and proposes the use of advanced classification techniques for web-based applications. As a result, their own web page has been built. Li et al. [3] created their own dataset by collecting a total of 271 soil samples from different provinces of China. Those samples were categorized into six different land cover types. They used the visible near-infrared spectroscopy technology and established a Convolutional Neural Network model for classification. The study aimed to find the impact of various amounts of training data on the CNN model and to compare its accuracies with those of the SVM. On the other hand, the effectiveness of the Kennard-Stone Algorithm (K-S algorithm) and the random method for dividing the training dataset were also highlighted by this paper. The paper reported: When the calibration set size decreased from 150 to 100, both CNN and SVM achieved 100% accuracy on the test set. However, with a further decrease from 90 to 40 samples in the calibration set, SVM showed a slight decrease in accuracy to 98.89% for 90 samples and 100% for the remaining. In SVM, the accuracy decreased with the decrease in the number of label samples. CNN performed better than SVM in classifying six different types of soil using the Kennard-Stone algorithm for calibration set division and achieved an accuracy of more than 95% on the test set. CNN also gave better classification results when random division ratios of 1/3 and 1/4 were used compared to SVM, with the accuracy of the test set being more than 87%. In 2021, Srivastava et al. [4] published a research paper on a comprehensive review of soil classification using DL and computer vision techniques. In this research paper, they created their own datasets and trained them using k-Nearest Neighbor (k-NN), Decision Trees (DT), SVM and CNN techniques. By using those techniques, they got an overall accuracy of 95.98% as a result. The results provided by this work give new insights into soil class mapping using the random forest model. Barkataki et al. [5] published a research paper on the classification of soil types from GPR B scans using DL techniques. In this research paper, they created their own datasets using an open-source electromagnetic simulator, gprMax, developed by the researchers at the University of Edinburgh, United Kingdom. In this dataset, they created a total of 700 scenarios for different soil types using various parameters. For this research, they used cross-validation techniques to train their datasets. Through this technique, they obtained an overall accuracy of 97%. Barman et al. [6] developed smartphone-assisted CNNs for the classification of soil texture in dry and wet humid conditions in West Guwahati, Assam, India. They constructed their datasets and trained the SCNN and MobileNetV2 models. They got testing accuracy of 99.62% for MobileNetV2 and 90%, for SCNN. Kim et al. [7] proposed a CNN-based framework for the estimation of soil water content and density in agricultural lands using photographs of the soil surface. In this research paper, the authors created their own datasets with the help of 60 digital images, used the AlexNet model for CNN-based image classification, and also used the CUDA and cuDNN techniques to enable GPU-based learning. By using these techniques, they got 97.5% accuracy for the 432x432-based model and 78.75% accuracy for the 864x864-based model. Azadnia et al. [8] used CNN and machine vision system based on images to predict soil texture accurately and fast. In this study, the authors suggested a CNN model with two blocks and numerous layers and built their own datasets. The first block is utilized for feature learning. The second block is a flattening layer and SVM classifier with fully connected layers. The results of the proposed CNN were compared with several classifiers such as ANN, SVM, RF, and k-NN. The proposed methods obtained an accuracy of more than 99%. Zhao et al. [9] constructed their own datasets and trained their CNN model. They achieved different accuracy for sand, clay, and silt soil types, such as 0.99, 0.98, and 0.98 for their proposed model. In 2022, Uddin and Hassan [10] published a research paper on a novel feature-based algorithm for soil type classification. In this research paper, they created their own datasets from different locations of Mymensingh Division, Bangladesh, and used four different machine learning (ML) models (SVM, ANN, MR, and DT); MATLAB's 10-fold cross-validation technique; and Quartile histogram-oriented gradients (Q-HOG) techniques. By using those techniques, they observed that the SVM model performs better than other algorithms; the best score is achieved by the SVM model, which is 80.74%, and the lowest is 77.35%. Vibhute and Kale [11] published a research paper on mapping several soil types using hyperspectral datasets and advanced machine learning methods. In this research paper, the authors created their own datasets and used satellite image processing, PLSR modeling for soil properties prediction, SAM, SVM, PCA, and MNF techniques to train their datasets. By using those techniques, they got a global accuracy of 86.84% and 91.77%, respectively. Chu et al. [12] published a research paper concerning the visualization and the accuracy enhancement of soil classification via laser-induced breakdown spectroscopy coupled with DL. In this research paper, the authors used datasets from the benchmark classification dataset for LIBS and supervised statistical learning algorithms like SVM, k-NN, DT, and ensemble learning to train their models. By employing those approaches, they achieved recognition accuracy rates of 97.29%, 86.79%, 85.69%, and 96.99% for the SVM, DT, k-NN, and RSM-EL models used in the recognition validation set, respectively. They obtained an average accuracy rate of 75.92% for the DNN model. Pandiri et al. [13] published a research paper for a smart system based on lightweight CNN for soil image classification. In this research paper, the authors have created their own dataset and trained it on a new lightweight CNN named the Light-SoilNet model. They achieved an overall accuracy of 97.2% with this technique on the proposed Light-SoilNet network architecture. Rahman et al. [14] designed a hybrid metaheuristic based on Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Then this PSO-GA had been utilized to optimize the DT for classifying the soil. The hybrid PSO-GA approach showed better performance in soil classification, with an accuracy of 96.04%, better than individual PSO, GA, and DT methods. Zhang et al. [15] developed a light-weight Vision Transformer integrating TinyViT's hierarchical compression with DropKey's dynamic sparse attention. This proposed design allows for high-precision soil classification in edge computing. The hybrid data augmentation method efficiently alleviates the class imbalance problem in soil datasets. The model reached 98.42% accuracy with only 5.40M parameters on 1915 soil imagery.

2. Methodology

The soil categorization algorithms have to undergo several steps before they can be put into operation. Fig. 1 shows the four steps of classification algorithms.

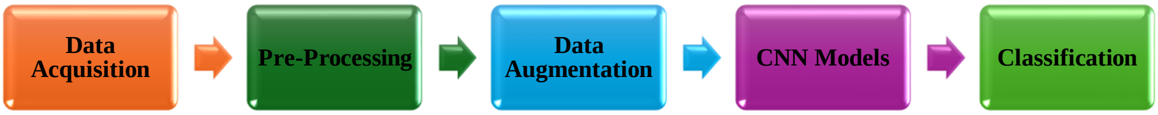


Fig. 1. Steps involved in implementing soil classification

2.1 Data Acquisition

For the classification of soils, five soil samples are collected from agricultural fields in various locations, covering three different ecological regions of West Bengal, such as West Midnapore, East Midnapore, and Purulia. The soil samples were obtained at a depth of 2–5 cm below the field surface. After collecting those samples, we grind them into small particles and arrange them according to their color in five different containers, which are shown below in Fig. 2.

Fig. 2. Five types of soil samples are arranged in different containers.

The dimensions of all the soil images are different due to the use of various types of mobile cameras, so first we change all the images' dimensions to 224x224 to reduce the computational complexity of the proposed models.

2.2 Data Augmentation

The performance of soil classification approaches depends on the accessibility of large amounts of data and the diversity of that data. However, collecting such enormous amounts of data depends on several considerations, such as the meteorological conditions and variations in sunshine. Data-augmentation approaches will be highly beneficial to address these challenges. Data augmentation is used to generate a large amount of data from a small amount of existing data. Based on dataset requirements, either basic data augmentation techniques or DL-based data augmentation techniques can be applied to augment the dataset [16]. In this work, we used five data augmentation techniques, such as RandomFlip, RandomRotation, RandomZoom, RandomHeight, and RandomWidth.

2.3 CNN Models

DL models can be utilized to execute feature extraction and classification to efficiently identify and classify soil types. Feature extraction refers to the process of capturing and representing the most important and suitable information from raw input data, and classification refers to the task of assigning a predefined label or category to an input based on that feature. In DL, both feature extraction and classification jobs are done by CNNs. CNNs can extract features independently, eliminating the need for manual extraction. The soil dataset was initially preprocessed and then expanded to 3703 images using data augmentation techniques. Later, for our research, we used five CNN models to train and extract the suitable features from the soil dataset for soil classification.

MobileNetV2 [17] is a well-known CNN architecture. It is designed for an efficient and lightweight DL model. It relies on an inverted residual structure wherein the residual connections are placed within the bottleneck layers. In this design, every input channel of MobileNet is assigned with one filter applied to depth-wise convolution. From this, the depth-wise separable convolution separates two layers, one for combination and one for filtering. The complete architecture of MobileNetV2 is composed of the first fully convolutional layer with 32 filters and 19 residual bottleneck layers.

ResNet50 [18] is a CNN that belongs to the ResNet (Residual Network) family. It is a mid-sized variant of the ResNet architecture. In this model, a conventional convolutional layer is followed by a max-pooling layer. It has four stages and sixteen residual blocks, varying the number of blocks per stage as the number of filters inside each block increases.

ResNet152 [18] is nothing but a deep convolutional neural network architecture of the ResNet family. It was introduced in 2016 to solve the problem of training very deep neural networks. The "152" in ResNet152 indicates that this architecture has a total of 152 layers, making it a very deep model. The depth of the network is achieved through residual blocks, which are shortcut or skip connections, to make it easier to train a very deep network.

InceptionV3 [19] is a convolutional neural network architecture from the Inception family for image classification and object detection tasks developed by Google researchers. It makes several improvements using label smoothing, factorized 7x7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network. Its modular design provides a good balance between computational efficiency and accuracy.

DenseNet201 [20] is a convolutional neural network architecture that belongs to the DenseNet (Densely Connected Convolutional Networks) family. In this architecture, the term 201 indicates a specific type of DenseNet with 201 layers, consisting of dense blocks with convolutional layers, batch normalization, transition layers that control spatial dimension, feature map number, and ReLU activation function. The total 552 image are partitioned into train data, test data, and validation data contain 70%, 20%, and 10% of the whole data, respectively.

3. Results

The experiment used a Windows 11 PC with 16 GB RAM, 64-bit OS, and 4 GB RTX GeForce 3050 GPU. The Keras 2.4.3 framework and TensorFlow backend helped train and validate DL models.

The dataset contains a total of 552 images captured using various mobile cameras. The original RGB images have different dimensions due to the usage of various devices, which were then set to 224x224. We divided the dataset into five different classes, such as Type 1, Type 2, Type 3, Type 4, and Type 5. Table 1 shows the details of the dataset. Then each class was divided into three parts: test data, train data, and validation data for model evaluation, where train data, test data, and validation data contain 70%, 20%, and 10% of the whole data, respectively. Table 2 describes the specification of the dataset.

3.1 Type 1 soil sample

It is collected from the agricultural land of Village-Agar, Post-Agar, District- West Midnapore, Pin-721222, West Bengal, India. After testing the soil sample, we found that it contains 1.14 ppm Zn, 1.92 ppm Cu, 0.55 percent organic carbon and 386 kg/ha N. The characteristic feature of this soil is the high content of aluminum oxide which gives the characteristic light color.

***Table 1**:* Number of images in each class present in the soil dataset

Soil Types	Number of Images
Type 1	109
Type 2	96
Type 3	137
Type 4	107
Type 5	103
Total	552

Table 2: Specifications Table of the dataset

Subject:	Environmental Science and Computer Science.
Specific subject area:	Soil Science, Soil Evolution, Climate ChangeType.
Type of data:	Image
How the data were acquired:	The total of five types of soil were collected from different locations in West Bengal. After collecting those soil samples, we captured a total of 552 images of soil at different angles and in various light conditions using various mobile cameras. Due to using various mobile cameras, we got different dimensions for every image. After this, we divided our images into five classes.
Data format:	Raw image of various types of soil.
Description of data collection:	Data is collected from various agricultural field of West Bengal.
Data source location:	The soil sample is collected from different location of West Bengal such as West Midnapore, East Midnapore, and Purulia.
Data accessibility:	DOI: 10.17632/6mx34nshm4.2 Direct URL to data: https://data.mendeley.com/datasets/6mx34nshm4/1ta

3.2 Type 2 soil sample

It is collected from agricultural land of Village-Khemasuli, Post-Khemasuli, District-West Midnapore, Pin-721513, West Bengal, India. The tested soil sample contains 2.29 ppm Zn, 5.08 ppm Cu, 0.63 percent organic carbon and 438 kg/ha N. The soil is of type of soil with gritty texture and good drainage capacity. It is mainly coarse particles (sand) with low content of organic matter and clay minerals.

3.3 Type 3 soil sample

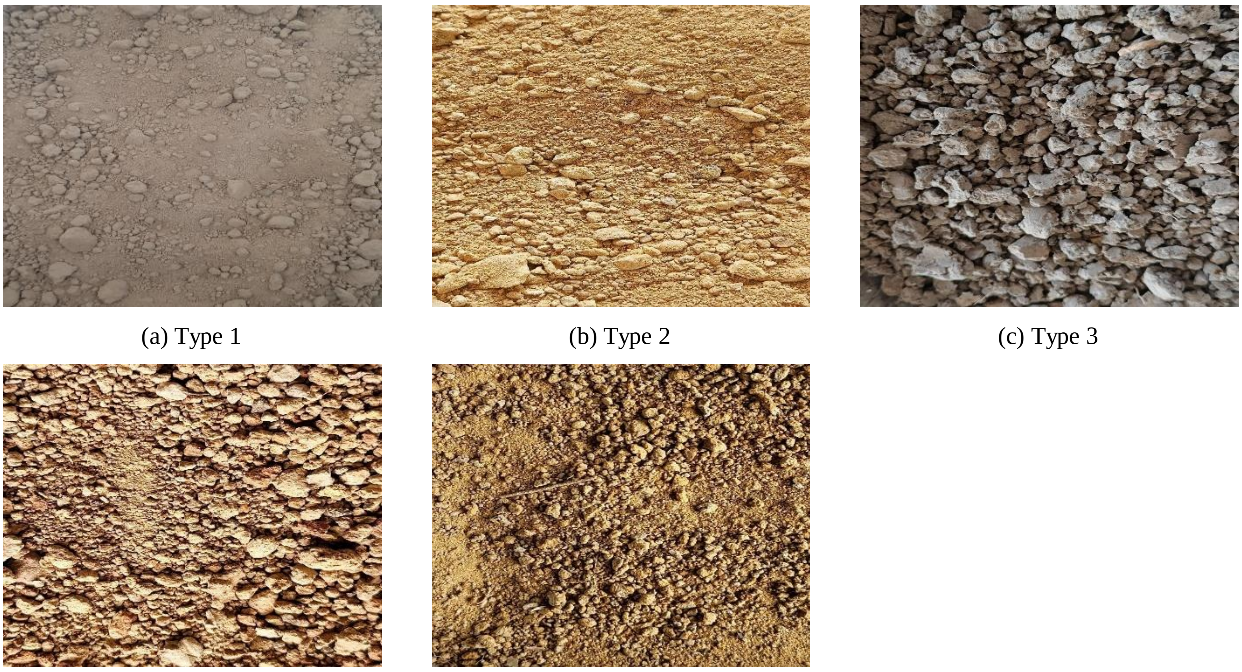
It is collected from the agricultural land of Village-Agar, Post-Agar, District-West Midnapore, Pin-721222, West Bengal, India. After testing this soil sample, we found that it contains 1.19 ppm Zn, 3.67 ppm Cu, 0.15 percent organic carbon and 107 kg/ha N. This type of soil is highly fertile and suitable for agriculture. It is mainly found in floodplains and coastal areas. It offers deep deposits which are ideal for cultivation.

3.4 Type 4 soil sample

The sample of soil is collected from agricultural land situated at Village-Kallabera, Post-Barakadam, District-Purulia, Pin-723129, West Bengal, India. After testing the soil sample, it was found to have 3.62 ppm Zn, 2.18 ppm Cu, 0.51 percent organic carbon and 355 kg/ha N. This is a kind of soil having fine texture and high clay content. This soil is formed from weathering of rocks rich in minerals like feldspar and mica.

3.5 Type 5 soil sample

Collected from the agricultural land at Village-Tunturi, Post-Tunturi, District-Purulia, Pin-723212, West Bengal, India. Testing this soil sample, we find that it contains 1.49 ppm Zn, 3.84 ppm Cu, 0.09 percent organic carbon, 107 kg/ha N. This is a kind of soil with a distinctive color and composition. It is generally found in temperate climate regions with moderate rainfall. The images of the collected five types of soil samples are presented in Fig. 3.



(a) Type 1 (b) Type 2 (c) Type 3

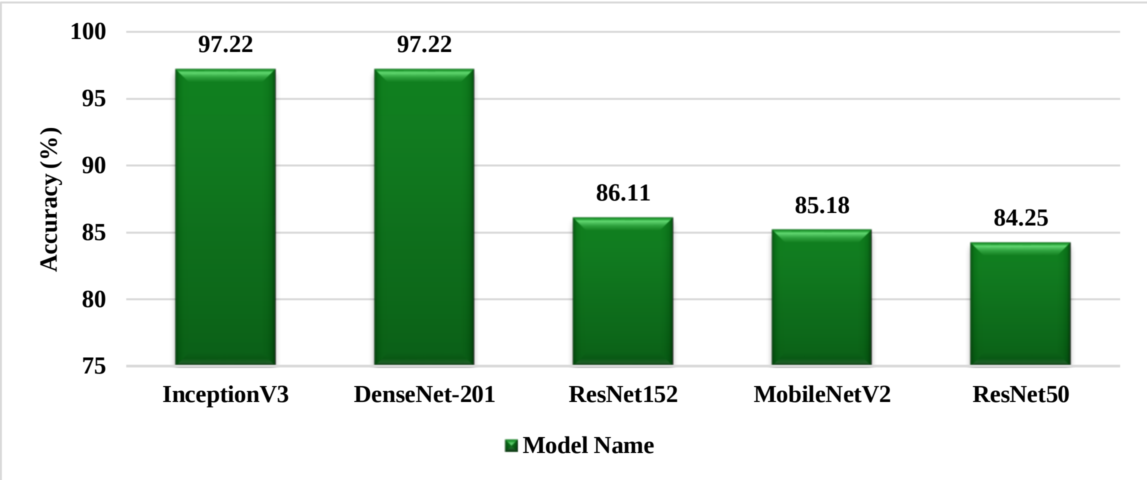
(d) Type 4 (e) Type 5

Fig. 3. Images of Collected Soil Samples

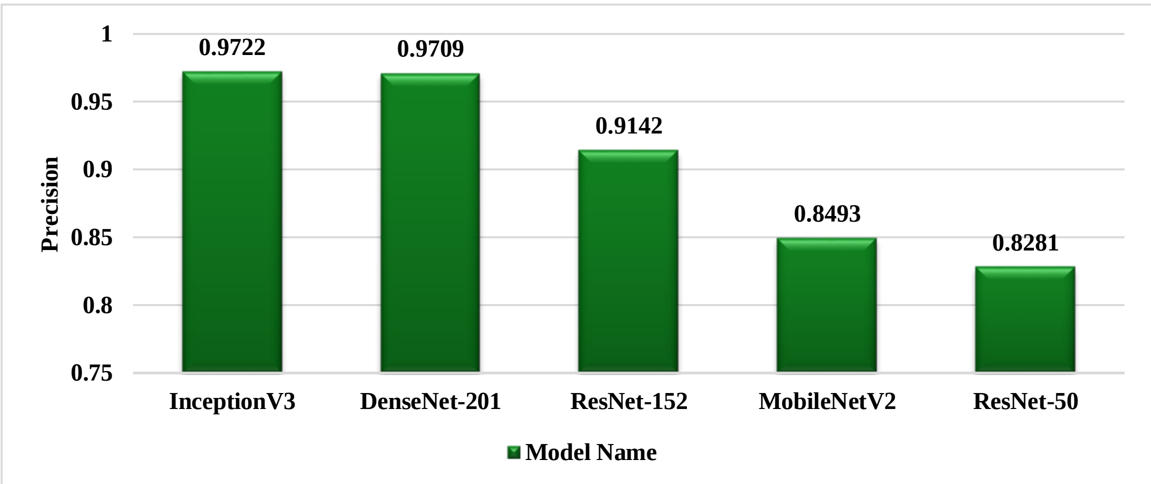
The classification performance results of the tested five CNN models have been measured by computing the accuracy, precision, recall, F1 score and the confusion metrices [21, 22]. The greater values of accuracy, precision, recall, and F1 depict superior classification outputs [21, 22]. The numerical values of these parameters of the tested CNN models are reported in Table 3. The metrics show that InceptionV3 produces best results among the tested CNN models. On the other hand, ResNet50 provides worst results among all. For better comparison, the graphical presentation of the accuracy, precision, recall, and F1 score of the tested CNN models in best to worst order has been performed in Fig. 4. The confusion metrices of the five tested CNN models are presented in Fig. 5. It provides a visual table comparing your model's predictions against the actual ground-truth data. Confusion matrices also demonstrate that InceptionV3 and DenseNet201 performed well in our dataset.

Table 3: Average Performance value of the tested CNN models

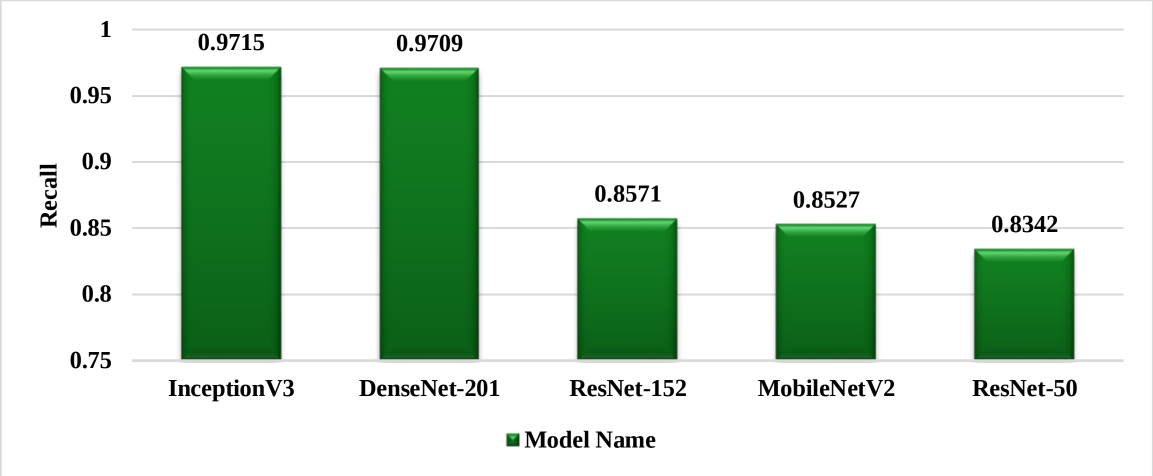
Model	Precision↑	Recall↑	F1 Score↑	Accuracy↑
MobileNetV2	0.8493	0.8527	0.8488	0.8518
ResNet152	0.9142	0.8571	0.8343	0.8611
InceptionV3	**0.9722**	**0.9715**	**0.9709**	**0.9722**
ResNet50	0.8281	0.8342	0.8287	0.8425
DenseNet201	0.9709	0.9709	0.9702	**0.9722**



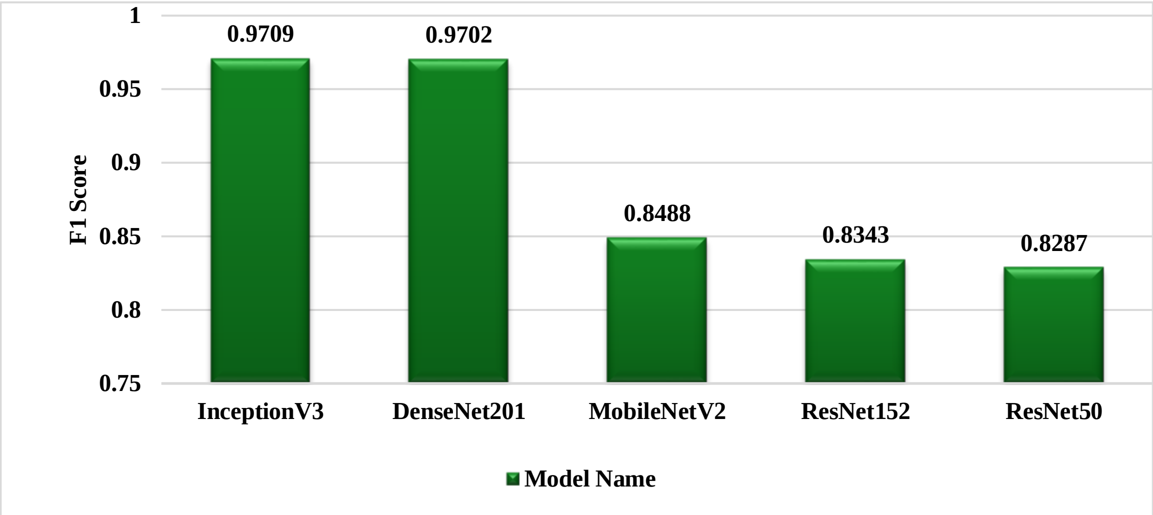
(a)



(b)

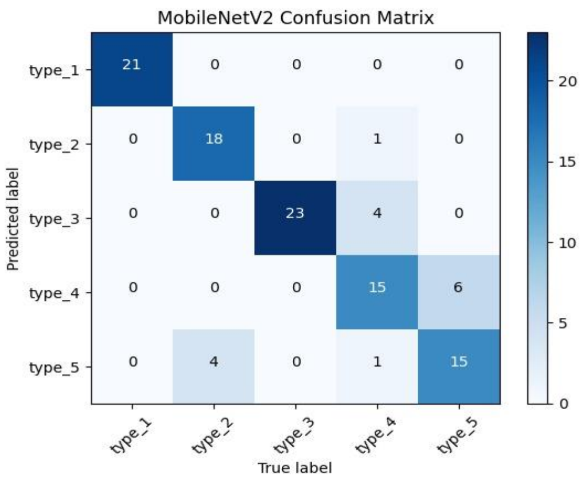


(c)

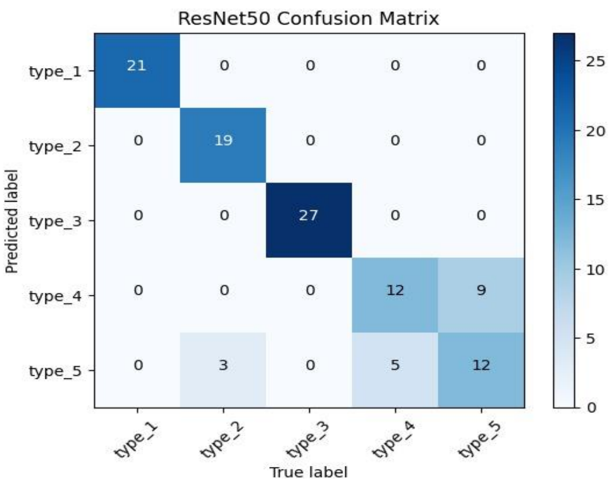


(d)

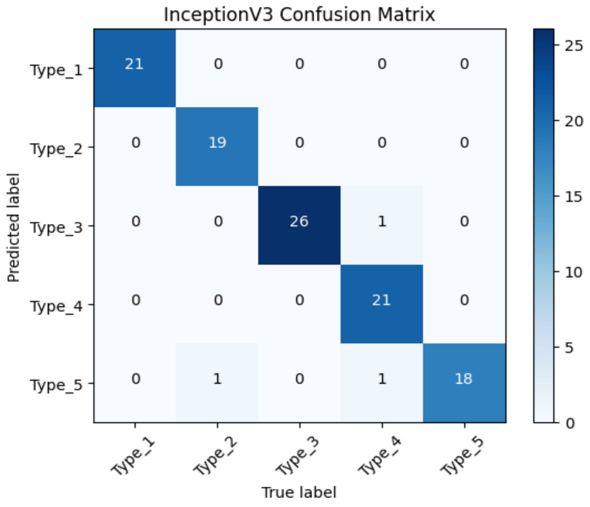
Fig. 4. Graphical comparison among CNN models: (a) Accuracy based comparison; (b) Precision based comparison; (c) Recall based comparison; (d) F1 Score based comparison.



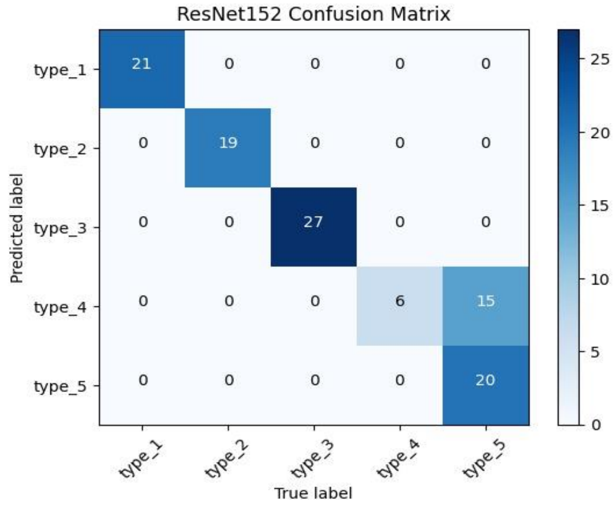
(a) MobileNetV2



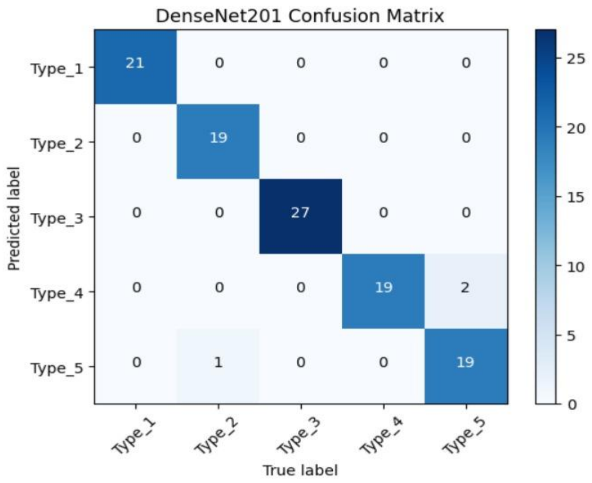
(b) ResNet50



(c) InceptionV3



(d) ResNet152



(e) DenseNet201

Fig. 5. Confusion matrices of the tested CNN models

4. Conclusions

Food demand is increasing on a daily basis as the population grows. Due to the increasing demand for food, it is necessary to classify the soil for proper crop selection, which will be beneficial for the farmers. Thus, this study demonstrates five CNNs-based frameworks for classifying the five types of soil images. The soil image dataset was created where soil images are captured by collecting soil samples from different agricultural lands in West Bengal, India. The six CNN models, such as MobileNetV2, InceptionV3, ResNet50, ResNet152, and DenseNet201, were used to classify five different types of soil. Then the performance of six different types of CNN models was compared, and we found that the highest accuracy score was in the InceptionV3 model with the highest precision, recall, and F1-score, and we also found the lowest accuracy in the ResNet50 model with the lowest precision, recall, and F1-score. Therefore, after analyzing those results, we found that InceptionV3 and DenseNet201 performed well in our dataset.

However, our proposed dataset has some limitations. All limitations are listed below:

- The dataset had 5 classes and only 552 images in total.
- The proposed soil samples are collected from a limited agricultural location in West Bengal.

Based on the conclusions and limitations, the following future research directions are proposed:

- Increase the number of images, and if possible, increase the number of classes, so that more soil types can be identified and help the farmers obtain more specific solutions.
- We are planning to develop our own model for this soil classification.
- Use other methodologies besides the CNN for the classification of the soil.

Declarations

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Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest. The authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Data Availability Statement: The data is open access.

URL to the dataset is: https://data.mendeley.com/datasets/6mx34nshm4/1ta.

Author Contributions: These Authors Contributed Equally.

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