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Research Article

Smartphone assisting convolutional neural networks for soil texture classification in dry and wet humid conditions in West Guwahati, Assam

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Abstract

Soil texture using a hydrometer or pipette method requires expertise, although these are accurate. A soil expert may help the farmer to detect the soil texture by analyzing the visual texture of the soil, which is not always accurate. This paper presents the smartphone image-based sand and clay soil classification in wet and dry humid conditions using Self Convolution Neural Network (SCNN) and finetuned MobileNet.A soil dataset of 576 soil images was prepared using a low-cost smartphone under natural light conditions. Different augmentation techniques such as shift, range, rotation, and zoom were applied to the soil dataset to increase the number of images in the soil dataset. The best performance of the MobileNet was reported at epoch 15 with a testing and training loss of 0.0091 and 0.0194, respectively. Though the SCNN model performed best at epoch 10 with a testing accuracy of 99.85%, the MobileNet reported less computation time (167.8s) than the SCNN (273.2s). The precision and recall of the models were 99.62 (MobileNet) and 99.84 (SCNN). The accuracy of the SCNN reported itself as the best model, whereas the computing time of the MobileNet reported itself as the best model in different humid conditions. The model can be used to replicate the traditional soil texture analysis method and the farmers can use it for better productivity.

Keywords: CNN, Image processing, MobileNet, Precision farming, Soil texture

INTRODUCTION

The productivity of farming depends on the selection of physical and chemical properties of soil, selection of seed, a good amount of plant photosynthesis, plant diseases, etc. Among these serious factors of farming, the soil factors should consider more seriously to get more productivity. A farmer should have the minimum knowledge about the soil texture and select the best suitable soil for cultivation. If a farmer does not know about the soil type and its texture, it may reduce the overall productivity of farming. The soil texture depends on the percentage of sand, silt, and clay in the soil. Light soil contains more sand than clay but heavy soil contains more clay than sand. So, the basic component of soil is clay and sand. All types of soil textures may not be good for all types of farming, such as sandy, sandy loam, and loam are good for citrus farming, but silty soil is not good for citrus farming (Yu *et al*. 2006). A specific soil is always good for a specific type of farming. Soil experts help farmers to identify the texture of the soil using modern laboratories or by viewing the visual texture of the soil. Modern techniques such as hydrometer and pipette are not cost-effective and they require the United States Department of Agriculture (USDA) triangle for the final soil texture analysis (Barman and Choudhury, 2019). These techniques demand expertise and time. These are serious issues from the farmer's point of view. To overcome these issues, the paper presents a soil texture analysis system using lightweight Convolution Neural Network (CNN) architectures from Smartphone images.

The application of different machine learning techniques for soil texture classifications has already been focused on earlier. Sun *et al*. (2004) used the Gabor wavelet frame with 4 scales and 6 orientations to classify the 3 soil texture classes. They captured the soil images using a digital camera with a single-camera setting. Extracting soil attributes using Digital Elevation Model (DEM) from the high-resolution soil map, Zhao *et al.* (2009) reported the Artificial Neural Network (ANN) to classify the clay and sand soil with an accuracy of 88% and 81%, respectively. The performance of the Support Vector Machine (SVM) classifier for sand, silty, and peat soil classification was reported by Srunitha and Padmavathi (2016). Mengistu and Alemayehu (2018) from Euthopia reported a hybrid approach to soil texture analysis by using ANN with an accuracy of 89.7% for 7 different types of soil texture with the co-occurrence texture analysis. A study was reported in china for 3-class soil classification by Wu *et al.* (2018) using SVM, ANN, and Decision Tree (DT) with an accuracy of 79.4%, 99.2%, and 66.1%, respectively. In 2020, de Oliveira Morais *et al*. (2020) used Support Vector Regression (SVR) and Linear Regression (LR) for soil texture analysis. Among all the traditional methods, the use of the SVM classifier (Barman & Choudhury, 2019; Srunitha& Padmavathi, 2016; Wu *et al.,* 2018) was more in soil texture classification.

Researchers also focused on CNN in soil texture classification along with the traditional machine learning methods, but the applications are very limited. In 2019, Riese and Keller (2019)reported using CNN with an accuracy of 72% for classifying 4 different types of soil texture.Anandan(2021) extracted 84 different soil attributes by applying the Particle Swarm Optimization (PSO) based CNN architecture on the Lucas dataset. Wadoux (2019) also investigated the Lucas dataset for soil mapping.

It was noticed that the researchers used either a public soil dataset or captured the soil images using a high-end digital camera. These methods were not cost-effective from the farmer's point of view. To reduce the system cost and benefit farmers, the present study reports Smartphone image-based soil texture analysis using lightweight CNN so that the investigated model can easily load in a Smartphone application for the easy use of farmers. The studied system forwards the contributions towards digital farming using deep learning techniques as i) A robust digital soil image dataset was prepared using a Smartphone in a natural light condition, ii) Two types of CNN models were reported for sand and clay soil texture analysis and iii) Computational performance of the MobileNet and Self Convolution Neural Network (SCNN) were evaluated and reported to select the best model for soil texture analysis.

MATERIALS AND METHODS

About the dataset

The paddy fields of the west Guwahatiregions, Assam, India, were selected for the study. A total of 576 soil samples were collected using a Smartphone. A minimum of 200m distance between the two sample collection sites was maintained to get the different soil images. The soil samples were collected from the 6 inches depth of the soil surface and kept ready for image acquisition using a single Redmi Smartphone camera. The images were captured in wet and dry humid conditions to make the variations in the images (Fig. 2). All the images were photographed in natural light by maintaining18 inches distance between soil samples and the camera lens in a vertical position with the help of the Easy Measure mobile application.

In parallel, the textures of the soil samples were analyzed using the hydrometer. The meter was calibrated using a solution of sugar (28 grams) and distilled water (176 grams) (Barman and Choudhury, 2019). After the calibration, the fraction of sand, silt, and clay was determined using the equations (1-3), and finally, the actual texture of the soil was calculated using the USDA triangle. Four types of soil textures, i.e. sandy (289 soil samples), clay (291 soil samples), sandy clay (6 soil samples), and loamy sand (2 samples)were reported in the hydrometer test. As the number of sandy and clay soil samples was more than silty and sandy clay in dry and wet humid conditions, this research considered only these two classes of soil for classification. The sandy soil was labelled as 0, whereas the label of the clay soil was 1.

% Clay Portion = Hydrometer readings at 6hrs, 52 min* 100/wt of soil sample Eq. 1

% Silt Portion = Hydrometer readings at 40 sec*100/wt of soil sample-% of clay Eq. 2

% Sand portion = 100%-%Silt-%Clay Eq. 3

In Fig.1, the blue points in the triangle denote the sand, whereas the yellow points denote the clay soil. The green and red points denote the sandy clay and loamy sand. Due to very few soil samples being in the loamy sand and sandy clay category, the entire soil dataset was highly imbalanced. So the images of these two categories were not considered in training and testing.

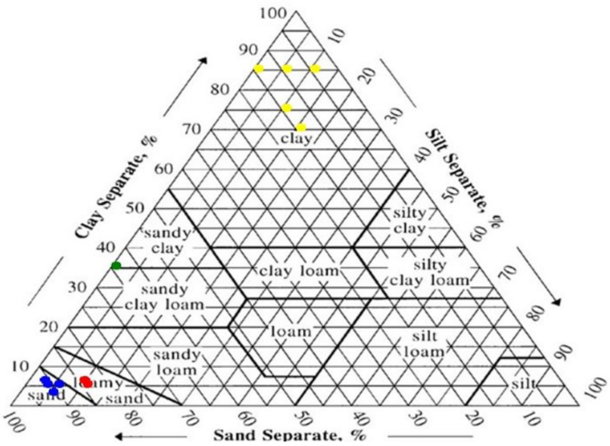

Fig. 1. *USDA soil triangle for consideration of soil texture*

Step 1.1: Rescale the soil image by 1. /255
Step 1.2: Rotate the soil image by keeping the rotation range = 40
Step 1.3: Consider the Horizontal Flip=True
Step 1.4: Perform the Width and Height Shift Range of the soil image =0.2
Step 1.5: Consider the shear and zoom range of the soil image =0.2
Step 1.6: Consider the Fill Mode of the soil image ='nearest'
Step 2: End

After the augmentation, a total of 13095 images were generated for the entire soil dataset. (Fig. 3) where 6555 images were in Clay and 6540 images were in sand class. Out of the 6555 images of clay, 3225 images were dry clay soil and 3330 images were wet clay soil. Like, a total of 3420 images of sand were dry sandy soil, and 3120 images of sand were wet sandy soil. The division of training and testing sets of the soil dataset is presented in Table 1.

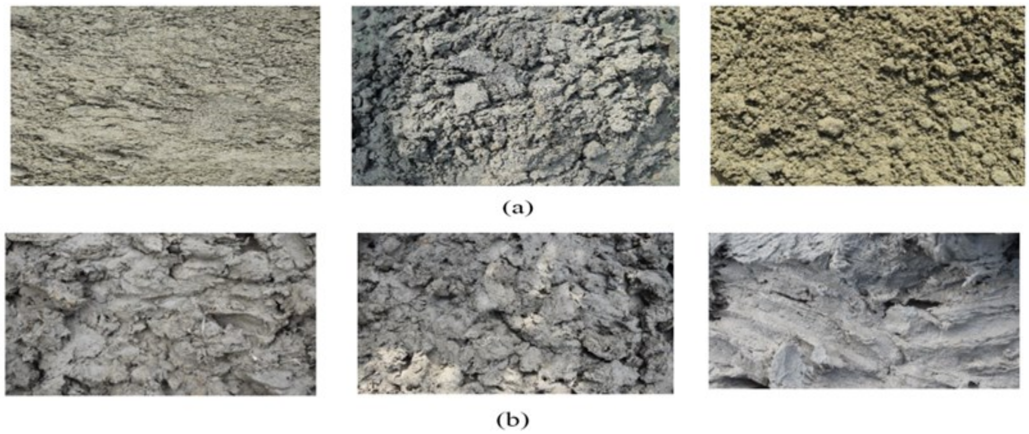

Fig. 2. *Some of the samples of a) Sandy Soil and b) Clay Soil collected from the west Guwahati region of Assam*

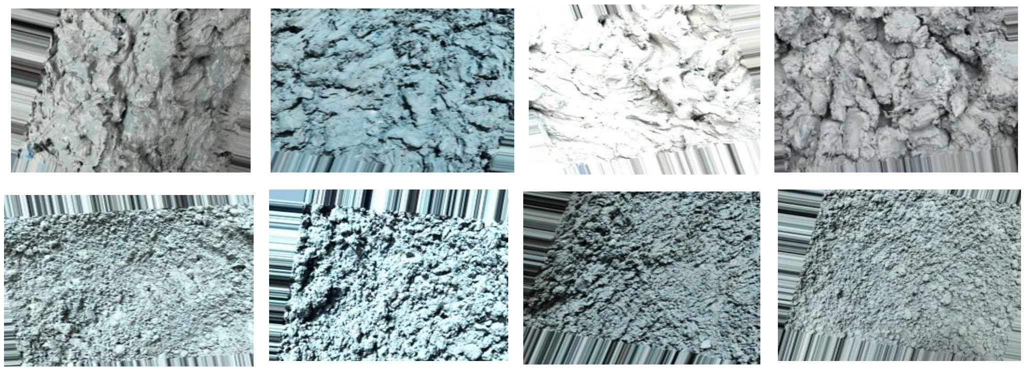

Fig. 3. *Some examples of the augmented soil images*

Preprocessing of soil images

A smartphone camera with default camera settings was used to photograph the images (Barman *et al.,* 2018). The camera recorded the images of the soil in a high dimension (3120x4160). The images were reduced to a new size of 224X224 because the high-dimensional images take more processing time than the low-dimensional images. Since the dataset contained a limited number of images, it was augmented to increase the number of training and testing samples of soil by considering the following steps.

Steps for soil image augmentation:
Step 1: Tale a loop i=1 to 36 and do

Soil texture classification using mobileNet

The concept of transfer learning of CNN is broadly used in different interdisciplinary areas. In transfer learning, a pre-trained model is used to extract the features of the images and then the images are classified. In this study, the features of the soil images were extracted using the MobileNet V2, and then the soil images were classified by finetuning the model. The finetuning of MobileNet V2 was implemented using the tensor flow Hubin the Google Collab environment. Along with the actual structure of MobileNet V2, two dense layers and two dropouts were added to the model. The first dense layers consisted of 512 hidden neurons with the Relu Activation function. The dropouts were added to reduce the possible overfitting of the model and also to reduce neuron co-adaptation during the learning process. The first dropout was used to drop 40% of the total hidden neurons before the first dense layer. The second dropout was also used to drop 20% of neurons before the final dense layer. The final dense layer classified the two classes of soil texture with two hidden neurons and a sigmoid activation function. With the help of the ADAM optimizer, the MobileNet was compiled for 15 epochs because the ADAM combines stochastic gradient descent (SGD) with momentum and RMSProp.The SGD with momentum uses the faster convergence towards minima and the RMSProp of ADAM considers the exponential moving average. The present study considered a learning rate of 0.001 for the compilation and the losses were calculated using the binary cross-entropy loss. For model learning, the hyperparameters presented in Table 2 were considered. The algorithmic step of the MobileNet V2 (finetuned) is presented below (Fig. 4).

Soil texture classification using SCNN

In the present study, a new model, i.e. SCNN, was introduced to classify the soil texture. For the training and testing, 11785 images of soil were used in training and 1310 images were used in testing (Table 1). For training purposes, the images were again resized into a dimension of 100x100 from a dimension of 224X224 to reduce the processing time. The SCNN model (Fig.6) was compiled by considering the hyperparameters defined in Table 4. The model was trained for 10 epochs with a learning rate of 0.003 and a batch size of 32. The present study uses different learning rates and epochs for SCNN because the learning process of SCNN was different from MobileNet CNN. The algorithmic structure of MobileNetwas more complex than the SCNN, only it fits well with a lower learning rate than the SCNN. With this learning process, a total of 33,878,394 parameters were evaluated, and the learning steps are defined below.

RESULTS AND DISCUSSION

The results of both MobileNet CNN and SCNN are presented in Table 6 and Table 7. Table 6 represents the training and testing accuracies of the MobileNet CNN per epoch, whereas Table 7 represents the training and testing accuracies of the SCNN per epoch.

Table 6 shows that the training and testing accuracies of the MobileNet were more than 90% from epochs 1 to 15. The model performed well in soil classification. The model maintained 90% accuracy in all epochs (Fig. 6). The average training accuracy for the model considering all epochs was 98.63%, with an average testing accuracy of 99.62% (Table 6). The model's losses were very few from epochs 1 to 15 (Table 6). The model's average training and testing loss were 0.0.03848 and 0.01078 (Table 6). These values indicated that the model was neither overfitted nor under fitted. The best performance of theMobileNet was achieved at epoch 15 with a training loss of 0.0194, training accuracy of

Table 1. Ratio of training and testing set after augmentation of soil samples

Original Soil Image	Augmented Soil image	Clay Image after augmentation	Numbers of Dry and Wet Clay Soil	Sandy Image after augmentation	Numbers of Dry and Wet Sandy Soil	Training (90%)	Testing (10%)
576	13,095	6555	3225 Dry 3330 Wet	6540	3420 Dry 3120 Wet	11785	1310

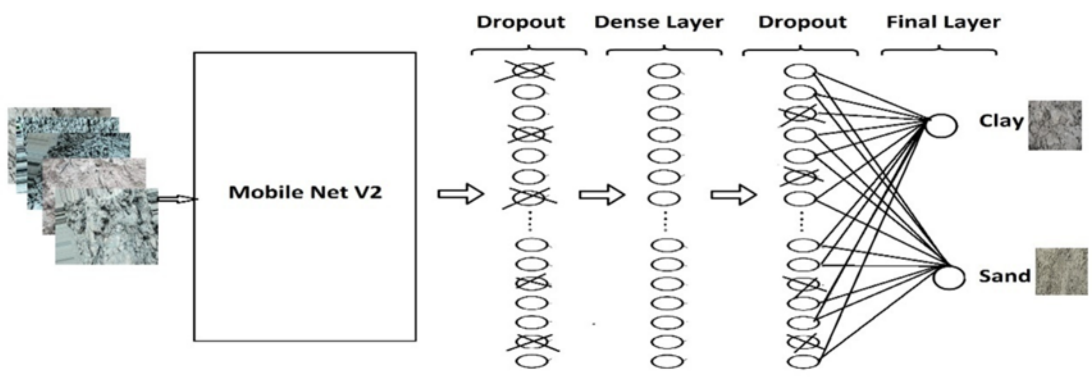

Fig. 4. *Block diagram of MobileNet V2 finetuned for soil texture classification*

Table 2. Hyperparameters of MobileNet CNN

Parameters	Purpose	Value
∞	Learning rate or Step Size	0.001
β1	Average gradients decay rate	0.9
β2	Average gradients decay rates	0.999
ε0	Positive constant to ignore the 'division by 0' error	10−8
Epoch	The number of the cycle for training	15
Batch Size	To Control the accuracy of the error gradient	32
Optimizer	To optimize the Model during error estimation	ADAM

Table 3. Model summary of finetune MobileNet2 for soil texture classification

Layer	Output	Parameter
MobileNet V2 layers (Sandler *et al.* 2019)	(None, 1280)	3.4 million (34, 00,000)
Dropout	(None, 1280)	0
dense_1 (Dense)	(None, 512)	655872
Dropout	(None, 512)	0
dense_1 (Dense)	(None, 2)	1026

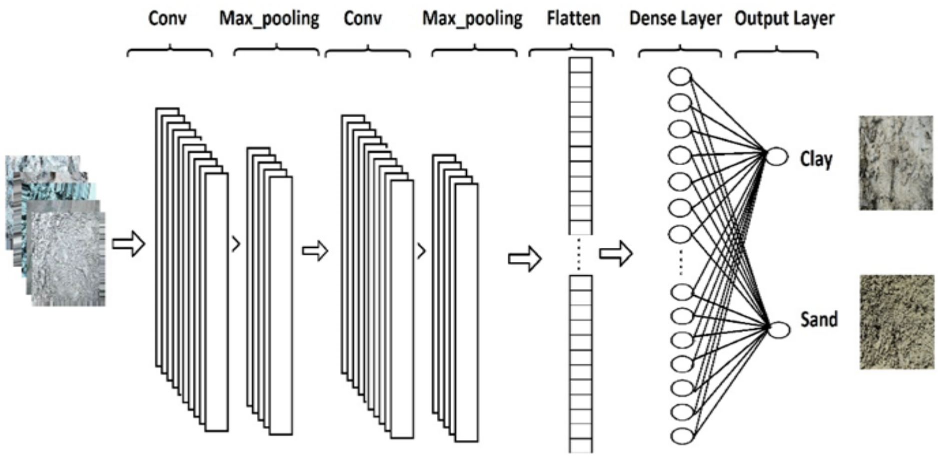

Fig. 5. *Block diagram of SCNN for soil texture classification*

Table 4. Hyperparameters of SCNN for soil texture classification

Parameters	Purpose	Value
∞	Learning rate or Step Size	0.003
β1	Average gradients decay rate	0.9
β2	Average gradients decay rates	0.999
ε0	Positive constant to ignore the 'division by 0' error	10−8
Epoch	The number of the cycle for training	10
Batch Size	To Control the accuracy of the error gradient	32
Optimizer	To optimize the model during error estimation	ADAM

Table 5. Model summary of SCNN for soil texture classification

Layer	Output	Parameter
conv2d_1 (Conv2D)	(None, 98, 98, 32)	896
max_pooling2d_1	(None, 49, 49, 32)	0
conv2d_2 (Conv2D	(None, 47, 47, 64)	18496
max_pooling2d_2	(None, 23, 23, 64)	0
flatten_1 (Flatten)	(None, 33856)	0
dense_1 (Dense)	(None, 1000)	33857000
dense_2(Dense)	(None, 2)	2002

99.26%, testing loss of 0.0091, and testing accuracy of 99.62%. The average training time of the model was 167.8s. Riese and Keller(2019) introduced Lucas CNN, Lucas Resnet, and Lucas Coord CNN to classify the soil texture on hyperspectral data. Since the Lucas soil dataset demanded a 1-D CNN classifier, they used the 1-D CNN model to classify 4 numbers of soil textures with71%, 72%, and 73% accuracies in Lucas CNN, Lucas Resnet, and Lucas Coord CNN, respectively. Anadan (2021) also reported 97% accuracy in the Lucas dataset for soil texture analysis using PSO-based CNN. In the present study, a smartphone soil dataset was used to classify the soil texture with an accuracy of 99.62% using the lightweight MobileNet CNN. Mengistu and Alemayehu (2018) determined 7 texture properties of the soil and classified the same using ANN with an accuracy of 89.7%. They captured the images of the soil by using a digital camera. The present study reported more accuracy than the accuracies of the investigation of Mengistu and Alemayehu (2018) because they focused only on the 7 different texture features which may miss some of the important features of the soil images.

Along with MobileNet, the present study also classified the sand and clay soil by using SCNN. The model performance is presented in Fig. 7. Table 6 shows that the training accuracies of the SCNN model were more than 90% from epochs 1 to 10. The testing accuracies of the SCNN decreased by 99.69% to 97.71% from epochs 5 to 6. At epoch 6, the training accuracy of the SCNN was 99.49% (Table 6). It was noted that the model was slightly overfitted at epoch 6. But the overfitting was reduced with the increasing of epochs. The average training accuracy of the SCNNconsidering all epochs was 98.60%, with an average testing accuracy of 98.25% (Table 7). Again, the loss curve (Fig. 7) shows that the losses of the model were very less from epoch 1 to 10, but testing loss slightly increased at epoch 7. The average training loss of the SCNN model was 0.03897, with an average testing loss of 0.05101 (Table 6). The best performance of the model was found at epoch 10 with a testing accuracy and loss of 99.85% and 0.0028, respectively. At epoch 10, the training loss of SCNNwas 0.0006 with a training accuracy of 100%. The average training time of the model was 273.2s.

From the results described above of MobileNet and SCNN, it is reported that the average performance of the evaluated models was more than the result of the investigations of Riese and Keller (2019). Wu *et al.* (2018) reported the application of SVM for soil texture classification, but their results were less than the results of the present investigation. Chung *et al.* (2010) reported 96% accuracy in digital camera-based soil texture classification. Swetha *et al.* (2020) reported a maximum of 98% accuracy for the classification of 3 soil textures using CNN. The models of the present

Table 6. Accuracy and loss of Mobile Net V2 CNN for soil texture classification

Epoch	Training Loss	Training Accuracy	Testing Loss	Testing Accuracy	Training Time (in Sec)
1	0.0729	0.9421	0.0192	0.9924	174
2	0.0393	0.9868	0.0155	0.9950	171
3	0.0308	0.9894	0.0125	0.9950	171
4	0.0341	0.9569	0.0092	0.9973	171
5	0.0249	0.9907	0.0106	0.9947	170
6	0.0227	0.9918	0.0095	0.9970	170
7	0.0202	0.9923	0.0089	0.9966	170
8	0.0154	0.9936	0.0137	0.9958	170
9	0.0230	0.9902	0.0108	0.9977	170
10	0.200	0.9936	0.0085	0.9973	168
11	0.0188	0.9943	0.0082	0.9977	164
12	0.0179	0.9940	0.0095	0.9970	163
13	0.0181	0.9927	0.0073	0.9973	162
14	0.0197	0.9935	0.0092	0.9973	162
15	0.0194	0.9926	0.0091	0.9962	161
Average	0.03848	0.9863	0.01078	0.996287	167.8

Table 7. Accuracy and loss of SCNN for soil texture classification

Epoch	Training Loss	Training Accuracy	Testing Loss	Testing Accuracy	Training Time (in Sec)
1	0.2315	0.9113	0.1039	0.9595	284
2	0.0578	0.9786	0.0950	0.9706	279
3	0.0180	0.9942	0.0070	0.9992	280
4	0.0095	0.9970	0.0139	0.9943	266
5	0.0062	0.9978	0.0116	0.9969	267
6	0.0169	0.9949	0.0702	0.9771	266
7	0.0216	0.9944	0.0148	0.9977	286
8	0.0132	0.9962	0.1870	0.9328	270
9	0.0144	0.9957	0.0039	0.9985	267
10	0.0006	1.000	0.0028	0.9985	267
Average	0.03897	0.98601	0.05101	0.98251	273.2

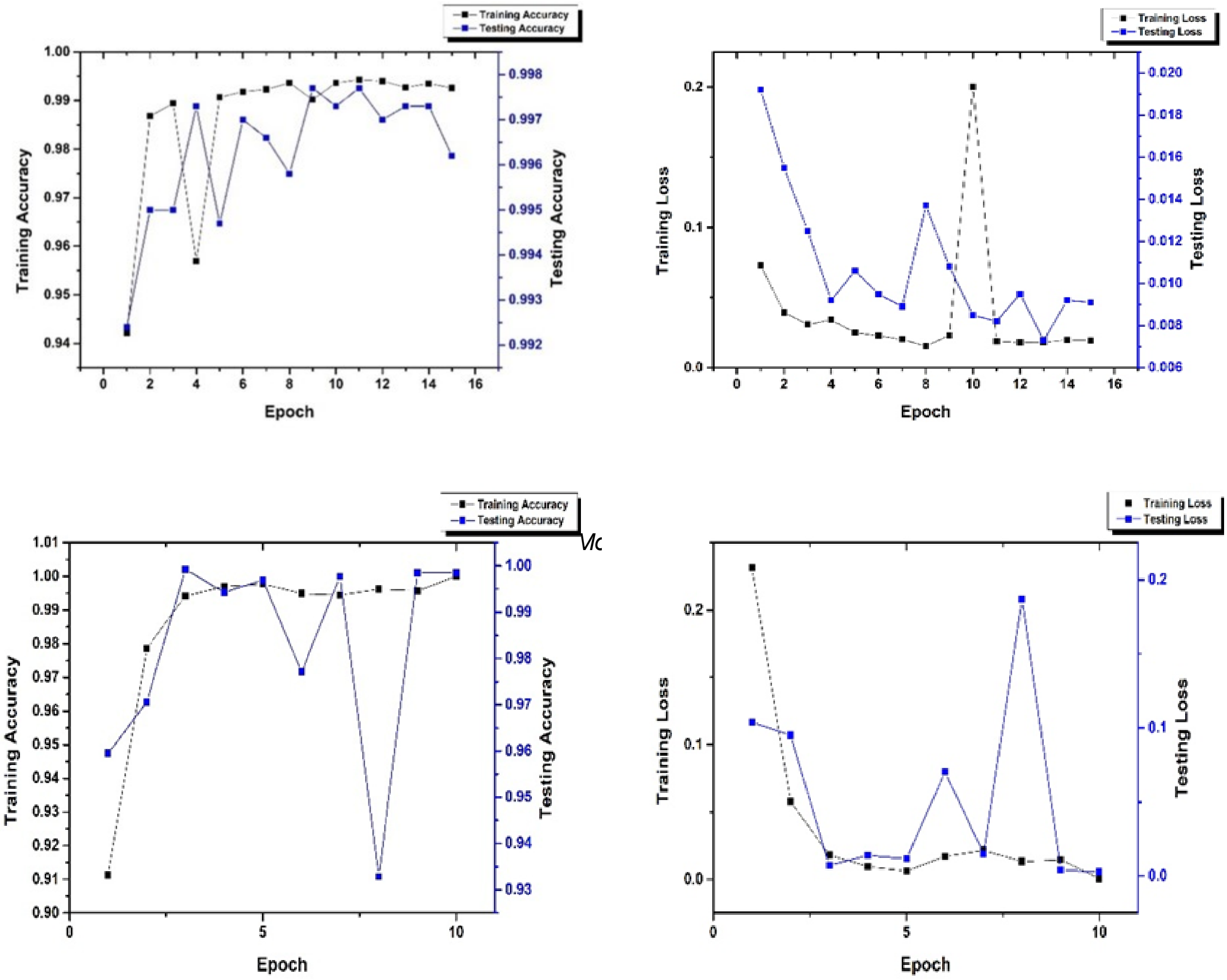

Fig. 7. a). *Accuracy and b) loss of SCNN for soil texture classification*

Table 8. Precision and recall of the soil texture classification

Model	Class	Precision	Recall
MobileNet CNN	Clay	99.69	99.69
	Sand	99.69	99.69
SCNN	Clay	99.84	99.84
	Sand	99.84	99.84

Table 9. Confusion Matrix of the soil texture classification

Model	Soil Type	Clay	Sand
MobileNet CNN	Clay	644	2
	Sand	2	662
SCNN	Clay	645	1
	Sand	1	663

Table 10. Comparative analysis soil texture analysis

Author(s)	Soil Class	Features	Algorithm	Accuracy
Riese and Keller, (2019)	4	Deep	CNN	74%
Wu *et al.* (2018)	3	DEM	Multi SVM	0.794 (Clay) 0.992(Loam) 0.661 (Sand)
Mengistu and Alemayehu, (2018)	6	Texture	BPNN	89.7%
Honawad *et al.* (2017)	Not Defined	Color	Similarity Check	Not Calculated
Srunitha and Padmavathi, (2016)	7	Color, texture	Multi SVM	60.9%
Guang *et al.* (2015)	7	DEM	Multi SVM	96.67%
Vibhute *et al.* (2015)	5	Texture	Multi SVM	71.78 %
Shenbagavalli and Ramar, (2011)	5	Color	Convolution	Not Calculated
Chung *et al.* (2010)	13	Color	LR	48%
Zhao *et al.* (2009)	2	DEM	ANN	88% (Clay) 81%. (Sand)
Bhattacharya and Solomatine, (2006)	3	Boundary Energy	ANN	91%
Zhang *et al.* (2005)	2	Texture	HMM and ML	100
Sun *et al.* (2004)	3	Texture	MVG	91%
(Swetha *et al.* 2020)	3	Texture	RF and CNN	clay (97% -98%) sand (96%-98%) silt (62%-75%)
Soil_Net (SCNN)	2	Deep Feature	CNN	99.62
Soil_Net (MobileNet)	2	Deep Feature	CNN	98.85

study evaluated by calculating the classification's precision, recall, and confusion matrix are mentioned in Tables 8 and 9.

The precision of the clay class was 99.69 in MobileNet CNN. It means that 99.69% of the clay data was perfectly classified. Again recall (99.69) denotes the number of positive clay class predictions out of all positive clay soil images. With a recall value of 99.69, the precision of the sand class using MobileNet CNN was 99.69. Again, with a precision of 99.84, the recall value of clay was 99.84 in the case of SCNN classification. The performance of the MobileNet and SCNN evaluated by using the unnormalized confusion matrix is given in Table 9. The confusion matrix presented the perfectly classified texture of the soil (sand and clay). It showed that out of 646 testing clay images, 644 images were perfectly classified as Clay and 2 images were misclassified as sand. Again, with the misclassification of 2 images, 662 images were perfectly classified as sand using MobileNet. In SCNN, a total of 645 images were perfectly classified as clay and 1 image was misclassified as sand. Using SCNN, out of 664 images of sand, 663 images were perfectly classified as sand, whereas 1 image was misclassified as clay. The comparative analysis of the different related works on soil texture classification is presented in Table 10.

Conclusion

The present study presents an image-based soil texture analysis to classify the soil images using CNNs. The images were captured using an android mobile phone camera within West Guwahati Region. Earlier reported, soil texture estimation methods were time-consuming and needed expertise. The present worked-out system takes a few seconds to classify the soil texture. Both the applied models, MobileNet and SCNN are acceptable due to low time consumption, low cost, and accurate result analysis. The present method does not require any expertise in the field. The results can be considered a replica of the traditional soil texture analysis method. The method can be directly used for texture classification before farming.

Conflict of interest

The authors declare that they have no conflict of interest.

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