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Original Article

Enhancing the Binary Soil Type Classification Performance with Augmented Data: An Eight-Layer Deep CNN and Pre-trained Models Investigation

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Abstract - *The image classification is a subset of computer vision. It relies on Deep Learning (DL) techniques driven by artificial intelligence (AI) to efficiently identify and categorize images. The main aim of this paper is to develop a classification system that classifies soil types based on soil color. Soil-type classification systems are greatly needed to analyze soil data and provide relevant agriculture-related information. However, there are no cost-free methods to classify soil type. Therefore, this research work proposes soil type classification system using an Eight-Layer Deep Convolutional Neural Network (ELDCNN) and compares its performance with six pre-trained models such as densenet121, mobilenetv2, inceptionv3, resnet50, vgg19 and vgg16. Additionally, this work examines the impact of normalization and data augmentation as pre-processing techniques applied to both the ELDCNN model and six pre-trained models to determine their effect on classification performance. Initially, normalization is applied to the original soil images, and both models are evaluated, resulting in lower classification accuracy. To address this, data augmentation is applied to expand the original soil image dataset while preserving the existing data, resulting in higher classification accuracy. The ELDCNN model with data augmentation achieved a test accuracy of 95%. It is 8% better than the ELDCNN on original images with normalization. Similarly, after augmentation, densenet121 obtained 88% accuracy among all pre-trained models. This accuracy is 1% better than the testing accuracy achieved by densenet121 on original images with normalization applied. The results show that data augmentation significantly improves classification accuracy compared to normalization for both models. Determining the soil type is best performed with the proposed ELDCNN model due to its optimal testing accuracy obtained through augmentation techniques.*

Keywords - *Image Classification, Normalization, Data Augmentation, Eight-layer Deep Convolutional Neural Network, Pre-trained Models.*

1. Introduction

Soil classification is an important task as it plays an essential role in agriculture. The soil is a place where crops grow. Soil type plays a major role in crop growth, which helps farmers decide what kind of crops will grow best and give high yields. Traditionally, soil types have been classified based on physical properties like texture, structure, color and mineral composition. These are important for understanding soil characteristics and play a key role in soil classification. Some common standard methods such as the Munsell color chart method, hydrometer method, pipette method and classification are based on USDA taxonomy, developed by the United States Department of Agriculture (USDA) are generally used. These methods rely on physical soil sampling, which can be time-consuming and costly. Compared to standard methods, an automatic prediction would be very important to reduce time and cost. As a result, the need for more efficient and scalable methods to classify soil types has driven the development of modern and digital techniques. Advances in remote sensing, machine learning, and image processing have led many researchers to explore various new methods for soil classification [1]. The soil classification using a munsell color chart based on artificial neural network and fuzzy logic [2]. The color sensors classify soil based on smartphone images [3]. A study [4] explored various machine learning algorithms for soil type classification by examining their accuracy and performance. The support vector machine achieved higher accuracy than other machine learning algorithms. The paper [5] proposed a soil classification method using image processing and Support Vector Machines (SVM) classifiers. The SVM classifier performed better than other classification techniques used in this work. A Deep Learning-based model using Convolutional Neural Networks (Vgg16, Vgg19, Inceptionv3 and Resnet50) for automating soil identification is proposed in [6]. Among all, Resnet50 achieved the highest accuracy of 87%, effectively classifying five soil types. The study [7] employed deep convolutional neural networks to classify various soil types from sentinel-2 satellite imagery data.

A region with only one predominant soil type and no other phenomena was chosen for the first study and got 95% accuracy. The location is combined in the second study with various soil types, in addition to other phenomena like large clouds. Compared to the first study, this one has a lower overall classification accuracy of around 92%. Based on the findings from various soil classification models, the current study proposed an *Eight-Layer Deep Convolutional Neural Network (ELDCNN)* model for soil type classification to obtain higher classification accuracy. CNN is a deep learning algorithm designed to effectively solve various problems in the agriculture sector. Therefore, this research work focused on a color-based soil type classification system using the ELDCNN model. A dataset of red and black soil images is utilized for this classification. The soil type classification system using ELDCNN will help farmers save money on fertilizers and chemical analysis because identifying the soil type prior to cultivation is essential for increasing the yield.

This work makes a significant contribution in the following ways:

1. This study aims to develop a color-based soil type classification system using ELDCNN as an alternative to traditional models.
2. The research compares the proposed ELDCNN model and six pre-trained models to assess which provides better and more efficient results in soil type classification. Normalization and data augmentation techniques are applied to both models to identify which technique leads to the best performance.
3. Evaluation metrics are then applied to demonstrate the effectiveness and quality of the models.
4. Based on the classification outcomes, the proposed ELDCNN model with data augmentation achieves the highest accuracy and efficiency in soil type classification.

The present study is set forth as follows: Various research works for soil classification are discussed in Section 2. Section 3 explains the soil classification and soil types in the study region. Section 4 introduced the proposed ELDCNN model, six pre-trained network models and performance evaluation measures. Section 5 demonstrates the results of the proposed techniques. Section 6 summarizes the research work and future enhancement.

2. Literature Review

Soil classification is a fundamental agricultural task that maximizes crop yields and manages land effectively. Traditionally, it was done either manually or by experts. But now, with new technologies and data availability, soil classification can be automated. Several techniques have been investigated to tackle the soil classification challenges, each with its own benefits depending on the type of soil data and specific needs. This study examines several of these methods and discusses them in the papers. Soil types affect crop growth, and understanding their characteristics is essential for agriculture. The research developed a suitable model that could classify a variety of soil series and recommend appropriate crops. The author used different machine-learning algorithms for soil classification, including weighted k-nearest neighbors, bagged trees and support vector machines based on the Gaussian kernel [8]. The study classifies soil using hyperspectral remote sensing and SVM. The classification identified five soil types, with brown sandy soil covering 51% and an accuracy of 71.18% [9]. Soil color provides key information about its composition and properties. The paper [10] developed an effective algorithm for detecting soil color through digital image processing. The images are labeled with Munsell soil notation, and the k-nearest neighbor classifier uses RGB values to classify them.

The study introduces an affordable digital soil classification system based on soil images for rural farmers. Fifty soil samples from West Guwahati, Assam, were captured and analyzed for texture using features such as HSV histograms, gabor wavelets, and discrete wavelet transform. The system achieved 91.37% accuracy with an SVM classifier, closely aligning with USDA soil classification results [11]. Soil classification is performed using genetic algorithm and fuzzy techniques, comparing and analysing the results [12]. An object-based classification method is used to classify very high-resolution images with machine learning algorithms like support vector machine, normal bayes, classification and regression tree and k-nearest neighbor for urban land cover classification [13]. The soil classification and crop suggestion are proposed in the paper [14]; color and texture features from soil images are extracted using hue saturation value, gray level co-occurrence matrix techniques and a decision tree algorithm is used for classification.

Using techniques from sensor networks and computer vision, the soil is characterized and classified. In this study, the authors have interfaced soil moisture sensors with Arduino-Uno and used image processing techniques. They have attained 87% accuracy with back-propagation neural networks in classifying soil samples [15]. In [16] focused on using convolution neural networks to classify soil images. According to the author, their research aimed to analyze many soils and recognize the red soil. After developing the model, the Flask framework creates a web application where users can upload images and get predictions about soil type.

Furthermore, when tried in the field, the outcomes are 91% accurate. Research on existing various soil classification models shows limited accuracy. Therefore, this study proposes an ELDCNN model for soil type classification to achieve improved accuracy.

3. Soil Classification

The soil is an indispensable thing for agriculture and is the real wellspring of nutrients used in crop development. The soil classification is done based on the appearance of soil in the agriculture field. The USDA developed the soil taxonomy, a system for classifying soils. According to the USDA taxonomy, the order in which the soil is classified is the most common degree of categorization. The soil order is classified based on soil qualities, horizon thickness, parent materials, drainage features, and landscape position. The range of soil orders includes inceptisols, vertisols, alfisols, oxisols, histosols, ultisols, podsols, mollisols, entisols, aridosols and spodosols [17]. According to USDA, the soils of Tamilnadu will come under entisols, inceptisols, alfisols, mollisols, ultisols and vertisols. In Tamilnadu, total coverage area of 36% was occupied by inceptisols, 30.5% by alfisols, 11.6% by vertisols, 7.4% by entisols, 3.3% by ultisols and mollisols was in very smaller amounts [18]. Soils are classified by the Indian Council for Agricultural Research (ICAR) into eight major categories: alluvial, black, red, laterite, desert, mountain, saline-alkaline and peaty [17]. Red gravel and clay loamy soils are the most common types of soils in Tiruppur district [19]. Apart from that, loamy, red loamy, black loam, sandy loam, gravel sandy loam, and clay soils are found in the district. This work used soil images of the Tiruppur district to classify soil types. Soil types in Tiruppur district are given in Table 1.

Table 1. Soils of Tiruppur district

Soil Types	Zone
Red Loam Soil	Avinashi, Palladam, Tiruppur and Udumalpet
Laterite Soil	Kangeyam and Dharapuram
Black Soil	Dharapuram, Avinashi, Palladam, Tiruppur and Udumalpet
Alluvium Soil	Palladam
Red sandy Soil	Dharapuram and Avinashi
Calcareous Soil	Avinashi, Palladam and Tiruppur

4. Proposed Methodology

In the current study, pre-processing, classification and performance evaluation are the three steps followed to classify soil types. The proposed workflow for this research is depicted in Figure 1. The proposed methodology for color-based soil type classification begins with pre-processing. This includes normalization to scale all the input soil images to ensure uniform pixel scaling across the dataset. Then, data augmentation techniques are applied to the original images to enhance the testing accuracy by providing the models with a broader and more varied dataset. The image data generator of class keras is used to transform the original images using rotations, flips, zooms, shifts, shearing and brightness. The image data augmentation techniques produced 700 new images from the existing 150 soil images. Following pre-processing, classification is done using the proposed ELDCNN model and six pre-trained models on original images with normalization and augmentation. The two models are compared based on their performance across various assessment measures.

4.1. Image Acquisition and Preparation

The Tiruppur district has been selected as the study area for the current research work. The 150 soil images collected from Udumalpet block, Madathukulam block and Gudimangalam block in Tiruppur district of Tamilnadu, India, are used. Soil images are acquired using a 13-megapixel smartphone camera under natural daylight conditions. The camera is positioned above the soil, kept level, and used to capture clear images without unwanted objects. All collected images are separated based on their colors. The images are classified into two distinct groups. Each group of soil has 75 images. The images are then labelled as Red soil and Black soil. The soil type classification task begins by splitting the dataset into train_test_validation sets. Splitting the dataset into distinct sets ensures that the models fit the new data effectively. It also supports accurate model evaluation. Thereby, the images are split into 60% for training, 20% for validation and 20% for testing. The collected original soil images used in this study are given in Table 2.

Table 2. Original soil images dataset

Dataset label	Training	Testing	Validation
Red Soil	45	15	15
Black Soil	45	15	15

4.2. Image Pre-Processing Techniques

The pre-processing is an image-processing step that reduces training time and enhances the classifier's accuracy. This work used normalization and data augmentation as pre-processing steps to increase the accuracy of the classifiers.

4.2.1. Normalization

Normalization is the first pre-processing step applied to the original soil image dataset. Normalization is used to alter the range of pixel intensity values. It ensures that each input image has a constant distribution in terms of size and pixel values. Min-max as a normalization technique is used in this work to scale image pixel values during pre-processing. The original pixel values of images range from 0 to 255. The min-max normalization method uses a scaling factor 1/255 to bring the pixel values into the (0, 1) range. However, its ability to improve classification accuracy is restricted when the dataset lacks adequate variability.

4.2.2. Data Augmentation

Data augmentation is applied as the next pre-processing step to address the normalization issues. This image pre-processing technique extends the dataset by applying some transformations to the images. The deep learning models require a massive amount of data, but due to the lack of a dataset, predictions may be imprecise and less accurate. In various deep learning-based image classification studies, several data augmentation methods have been shown to lower the model's error rate and broaden the dataset [20, 21]. Therefore, augmentation is desirable in this work to increase the quantity of original soil data. This study's training dataset consists of 150 soil images. The experimental dataset's richness is then increased by expanding these images using data augmentation techniques. The rotations, flips, shifts [22], brightness [23], zooms and shearing are applied to the gathered images. The image-augmented techniques used in this work are presented in Table 3. The images generated using Shear are 150, and Zoom produced 50 images. 100 images resulted from shifting, 100 by flipping, 200 images were created through rotation in both directions and 100 by brightness. The soil dataset consisted of 700 images after augmentation. The 700 soil images in the augmentation image dataset are divided into two groups, red and black, each with 350 images. Of these, 60% of the images are allocated to training, 20% to testing and 20% to validation. These 700 augmented images are applied to classify the soil type with the proposed ELDCNN model and six pre-trained models. The image data augmentation process and model design for soil type classification are given in Figure 2. The augmentation techniques are used to improve accuracy in soil type classification analysis. Table 4 shows the augmented original soil images considered for this study.

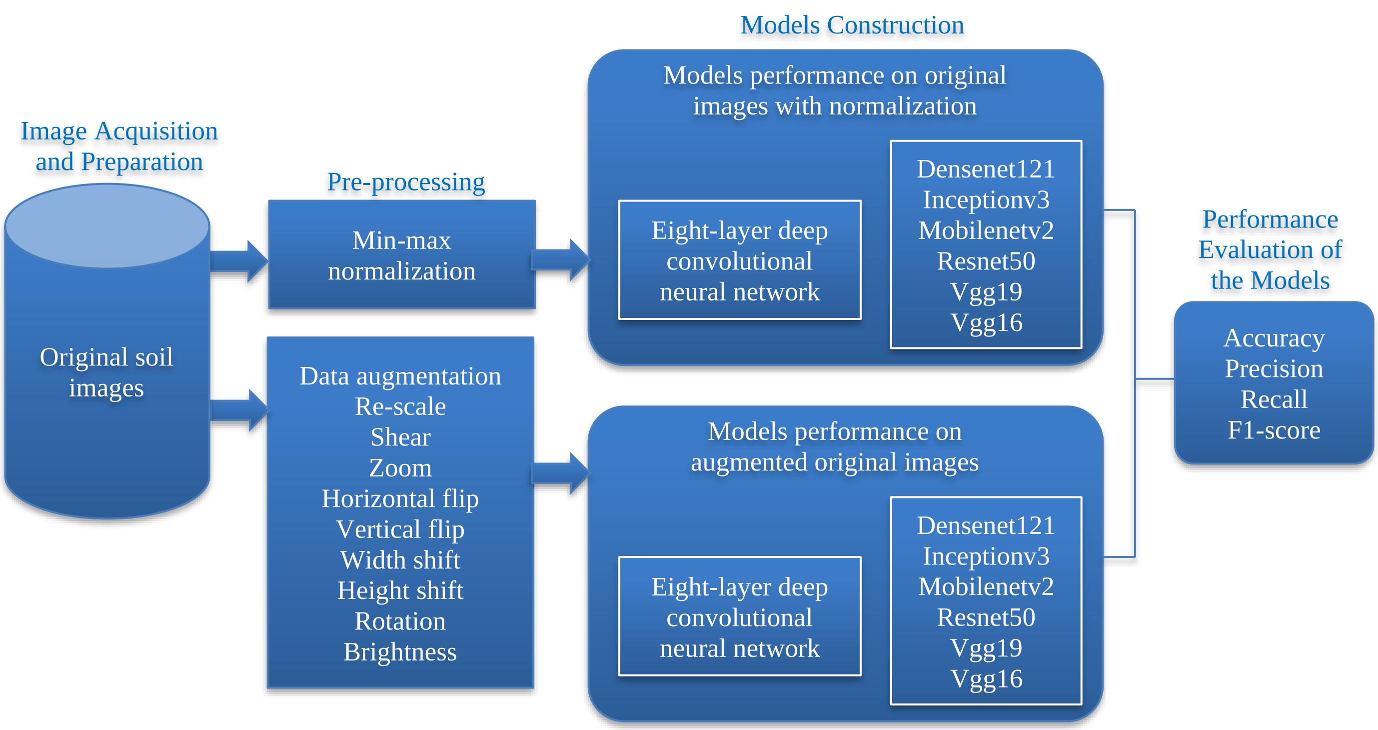


Fig. 1 Proposed workflow

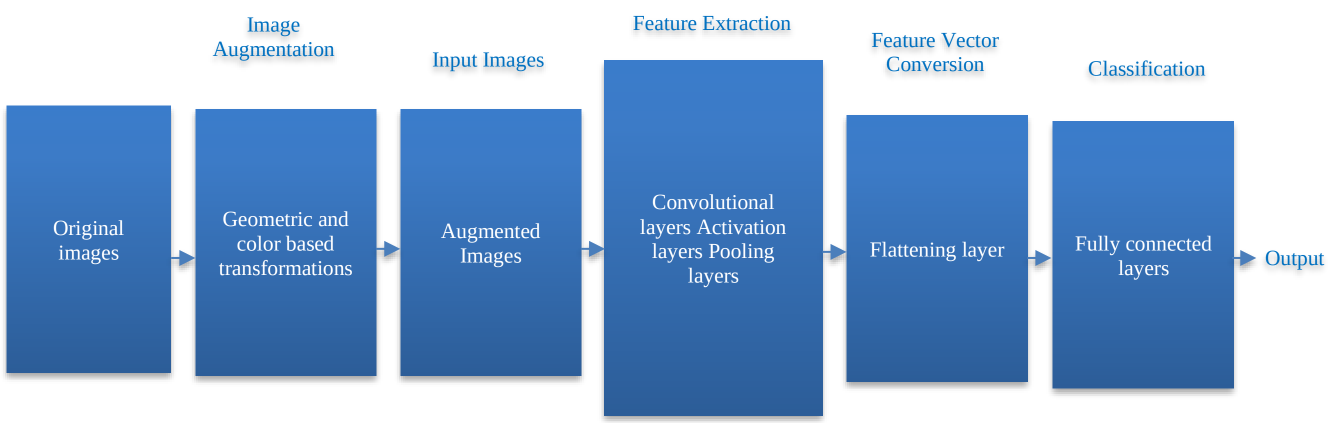


Fig. 2 Image data augmentation process for soil type classification

Table 3. Image augmentation techniques

Name	Ranges	Description
Re-scale	1./255	Rescaling converts the pixel in the range [0,255] to float [0,1]
Shear	0.2	Image is neither parallel nor particular in position
Zoom	0.2	Zooms the image to look smaller and bigger
Horizontal flip	True	The image is flipped horizontally
Vertical flip	True	The images flipped along its vertical axis
Width shift	0.2	The images are horizontally shifted either to the left or to the right
Height shift	0.2	Shift the image vertically to the top or the bottom
Rotation	15	Rotating the image in a clockwise or counterclockwise direction
Brightness	0.5,1.5	Adjust the brightness of the image

Table 4. Augmented original soil images dataset

Dataset Label	Training	Testing	Validation
Red Soil	210	70	70
Black Soil	210	70	70

4.3. Models Construction using Proposed ELDCNN and Pre-Trained Models

4.3.1. Proposed Eight-Layer Deep Convolutional Neural Network (ELDCNN) Model

CNN is the widely accepted effective learning algorithm. It has been used for tasks including image recognition [24], segmentation [25], and classification [26] and has shown exemplary performance in image-related tasks. The architectural design of CNN is largely based on the fundamental structure of the primary visual cortex, which was motivated by the author's work in [27]. Similarly, CNN follows the same structural design, which makes a convolutional operation to process the image and identify it based on certain features. An input layer begins a CNN, followed by several hidden layers and an output layer at the network's end. The convolution layers, pooling layers [24] and fully connected layers are the building blocks of CNN architecture. In the convolution layer, the filter will pass over the input image and scan the pixels to generate feature maps. The next step is the pooling layer, which reduces the number of pixels without losing the important function [28]. The maxpooling layer is used to hold the strongest pixels. The previous layer's outputs are flattened to be the input to the next level. There are two fully connected layers where the image classification actually happens. The first layer uses the input information from the prior layers and applies the necessary weights to determine the correct label. The second layer is an output layer where the images are predicted in corresponding classes. This work intends to propose an ELDCNN model for soil type classification. The proposed ELDCNN model employed in this study consists of an input layer, two convolutional blocks followed by convolution layers, maxpooling layers, a flattening layer, a dense layer and an output layer. The workings of ELDCNN architecture are represented below.

Step 1: Load the images of the soil as an input (a) to the input layer.

Step 2: An input image (a) is then passed to the convolutional layer (conv_1), where the filters (w_1) are convolved with the input images to find important patterns. The bias (b_1) is added, and the activation function relu is applied to the result of (w_1×a+b_1) as denoted in equation (1).

$$[conv\_1(a) = \{relu\}(w\_1 \times a + b\_1)] \quad (1)$$

This output goes through the maxpooling layer (max_1) and focuses on important features in the input images to generate the output. It is shown in equation (2).

$$[\mathrm{max\_1(conv\_1(a))}] \quad (2)$$

Step 3: The output of the convolutional block 1 passed to the convolution layer (conv_2) with filters (w_2) and bias (b_2). The output of the (conv_2) acts as an input for the maxpooling layer (max_2), which reduces the irrelevant features and selects the significant features. This is represented in equation (3).

$$[conv\_2(max\ \_1(conv\_1(a))) = \{relu\}\,(w_2 \times max\ \_1(conv\_1(a))) + b\_2] \quad (3)$$

Step 4: The flattening layer is added and takes the input from the (max_2).

Step 5: The first fully connected layer (f_1) consists of neurons (n_1), and the relu is assigned to the neurons as their activation function. This layer helps the network to learn the relationship among the features, which helps the model to understand the features that are significant for the soil type classification task.

Step 6: The last fully connected layer (f_2) consists of neurons (n_2), and the activation function relu is used. This final layer of an ELDCNN model is associated with the output layer, which is responsible for soil type classification.

Step 7: In training the output layer, the adam optimizer is used together with binary cross-entropy as the loss function. The ELDCNN model is trained with 20 epochs and a batch size 32.

The proposed ELDCNN first used original images with normalization for soil type classification. As its performance is average, augmented original images are used for the ELDCNN model to further improve its performance in soil type classification.

4.3.2. Pre-Trained Models

The six pre-trained models, in particular, densenet121, mobilenetv2, inceptionv3, resnet50, vgg19 and vgg16, are used initially for soil type classification with original normalized images. The input image is 224×224×3 pixels in size, and normalization is done for the input images. The models are trained with 20 epochs. With binary cross-entropy loss, the rmsprop optimizer is employed. The convolution process is applied to the input image to generate feature vectors as output. The extracted feature vectors from each pre-trained model serve as input to a fully connected layer to classify each image into corresponding classes. The classification results produced by the pre-trained algorithms are considerably low. Thus, data augmentation is utilized to improve the model's performance.

Densenet121

The densenet model was developed in 2017 [29], consisting of dense blocks with dense connectivity between layers, directly connecting all layers. In densenet121, the neural network count is indicated by the number 121. The densenet121 is more advanced than the resnet; it combines features by concatenating them. Instead of 'L' layers with 'L' links in traditional networks, densenet121 directs the $L(L+1)/2$ connections in the network.

The network has direct connections between each layer and every other layer. The input data from the first layer is accessible to even the last layer. This model is trained with the imagenet dataset. The image is resized to 224×224×3 in size. The features extracted by densenet121 through convolution and pooling layers facilitate the prediction of soil type.

Mobilenetv2

The mobilenetv2 by Google is based on a mobile terminal. The mobilenetv2 is similar to the original version, except it uses inverted residual blocks with depth-wise convolution layers. The model starts with a fully convolutional network layer consisting of 32 filters, 3×3 kernels and 2 strides in the first layer. Then, it is trailed by 19 residual bottleneck layers, a pooling layer, and a classification layer, which are the final layer without any non-linearity [30, 31]. This model, which had been trained on an imagenet dataset, was adapted to classify soil images in this study. The mobilenetv2 model accepts the image size as 224×224×3, and the final feature map has a shape of 3×3×1280. This model uses 1×1 convolution to expand the input channels. The second layer in this model is tasked with extracting features from the input using a deep convolutional layer. Then, the projection convolution layer lowers the network size.

Inceptionv3

The inceptionv3 is an upgrade of older versions from the inception family introduced by the authors in [32] from Google. In this model, convolution layers start in parallel and concatenate the layers called inception layers. Each layer has different filter sizes to extract the information from the images. Using factorization, the number of filters is reduced to simplify computation time. Between every convolution layer, there is a max pooling layer. The batch normalization and relu are added in the inceptionv3 model. This model considers 224×224×3 as the image size for the input layer and generates a features map of dimension 8×8×2048. The inceptionv3 model reduces the size of the grid, factorization into asymmetric convolutions, reduces the number of parameters participating, and makes larger convolutions to small ones, resulting in quick training and label smoothing to improve the error rate.

Resnet50

The authors in [33] proposed a residual neural network (Resnet) with 50 deep layers. The imagenet dataset consists of pre-trained weights used in this work. The model is not fine-tuned as it has the ability to provide useful features for most images. The resnet50 uses skip connections to pass information over layers. Skip connection allows information to travel faster in a network, and it aids the network in understanding image-level features. Additionally, it improves the easy recognition of visual content in images. The image is scaled to 224×224×3 to fit the input requirements of resnet50. The extracted image features from resnet50 are 2048-dimensional feature vectors.

Vgg19

The visual geometry group's vgg19 was introduced in 2014 [34]. It has 16 convolutional layers and 3 fully connected layers. The number of layers with trainable weights is represented by the number 19. The vgg19 model is composed of 5 blocks of convolutional layers, where the starting layer pair of convolutional blocks has 64 filters, then the following convolutional blocks use 128, 256 and 512 filters. Between each set of convolution layers, there is a max pooling layer. Three completely connected layers make up vgg19. The initial layers have 4096 nodes; the subsequent layer contains 1000 nodes, corresponding to the number of classes in the imagenet dataset. In this work, an image size of 224×224×3 is considered for this model, and it has the feature map size of 4×4×512.

Vgg16

The vgg16 has 3 fully connected layers and 13 convolutional layers. This model uses the activation function and max pooling layers to lessen the size of an image before adding the final fully connected layer. The authors in [34] made their proposal for vgg16 in 2014 and won the ILSVR (Imagenet competition). Both vgg16 and vgg19 are similar but differ only in total number of layers in a network [35]. The image size of vgg16 is 224×224×3 and has a 4×4×512 feature map. The classifier layer receives input from the extracted vgg16 features.

4.4. Performance Evaluation

The performance indicators are important to assess the effectiveness of the ELDCNN and six pre-trained models. Understanding how well the model works is essential after it has been constructed. Consequently, choosing the exact model is directed by the evaluation metric. Using the image classification methods, experiments are carried out with original normalized images and augmented original images. To thoroughly evaluate the performance of the suggested models, benchmark measurements must be used, including precision, accuracy, recall and f1-score.

4.4.1. Accuracy

The accuracy in equation (4) is the level of exactness of the expectations made by the model.

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{Total no of predictions}} \tag{4}$$

4.4.2. Precision

The precision refers to the fraction of true positives by anything predicted as a positive, as shown in equation (5).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

4.4.3. Recall

The recall measures how many positives out of all positives are expected, as shown in equation (6).

$$\text{Recall} = \frac{\mathbf{TP}}{\text{TP+FN}} \tag{6}$$

4.4.4. F1-score

The precision and recall function is represented by the f1-score, as shown in equation (7). False results, whether good or negative, are accepted.

$$\text{F1} - \text{score} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \tag{7}$$

5. Results and Discussion

ELDCNN is proposed for developing the classification model in the classification process, while six pre-trained models are employed only for comparison. Normalization and data augmentation are applied to both models to identify which techniques improve accuracy and optimize performance. The training parameters are set to train both models with a batch size of 32, 20 epochs and a dropout rate of 0.5. The activation function RELU and binary cross-entropy are used to compute the loss. The learning rate is given as 0.001, respectively. Adam optimizer is utilized for ELDCNN, and rmsprop optimizer is utilized for six pre-trained models. This work first normalized the original images and performed classification with the ELDCNN model and six pre-trained models, which resulted in various classification results. However, due to the tiny dataset, this study does have certain shortcomings. The data augmentation thus addresses this issue more effectively by applying augmentation to the original dataset. The ELDCNN and six pre-trained models used the expanded image dataset for analysis. Both works are compared. According to the results, the testing accuracy of ELDCNN with augmented images has increased from 87% to 95%.

Furthermore, augmentation techniques help to improve the accuracy of the pre-trained models, particularly the vgg16 model, by 9%. An experiment shows that the augmentation techniques have increased the testing accuracy of the ELDCNN model and six pre-trained models. The proposed ELDCNN with augmented images achieves the highest testing accuracy in soil type classification. The performance indicators are used to evaluate the proposed concept's efficiency.

5.1. Performance of ELDCNN and Pre-trained Models on Original Images with Normalization

All experimental studies are carried out in a Python environment. The six pre-trained models are represented in Figure 3, along with their training and validation accuracies on the performance of original images with normalization. As seen from the graphs, particularly densenet121, mobilenetv2, and inceptionv3 models achieved higher accuracy on training data, and their performance decreased when evaluating the unseen validating data. It is noted that the training and validation accuracy has more variance in their results because of the small dataset on which it was trained. Figure 4 depicts the loss values of the six pre-trained models' training and validation phases during the classification of original images with normalization. The training loss continues to decrease, whereas the validation loss increases, showing that the models are memorizing the training data rather than learning meaningful patterns. At the same time, the ELDCNN model performance is the same as that of six pre-trained models under similar conditions. There is also a considerable difference between training and validation accuracy. Similarly, the training loss is less compared to the validation loss, which exhibits the model's substandard performance. Normalization in this work adjusts only the values without adding different types of data variations. This leads to overfitting and low performance. The insufficient variations in the data and normalization restrict the models from reaching their best levels. The performance of the ELDCNN in terms of training and validation accuracy and loss on original images with normalization is depicted in Figure 5. According to Table 5, the experimental results show that the ELDCNN model has achieved a test accuracy of 87%. Also, the densenet121 test accuracy reaches up to 87%. Next inceptionv3 achieved 79% of accuracy. The resnet50 is good compared with mobilenetv2.

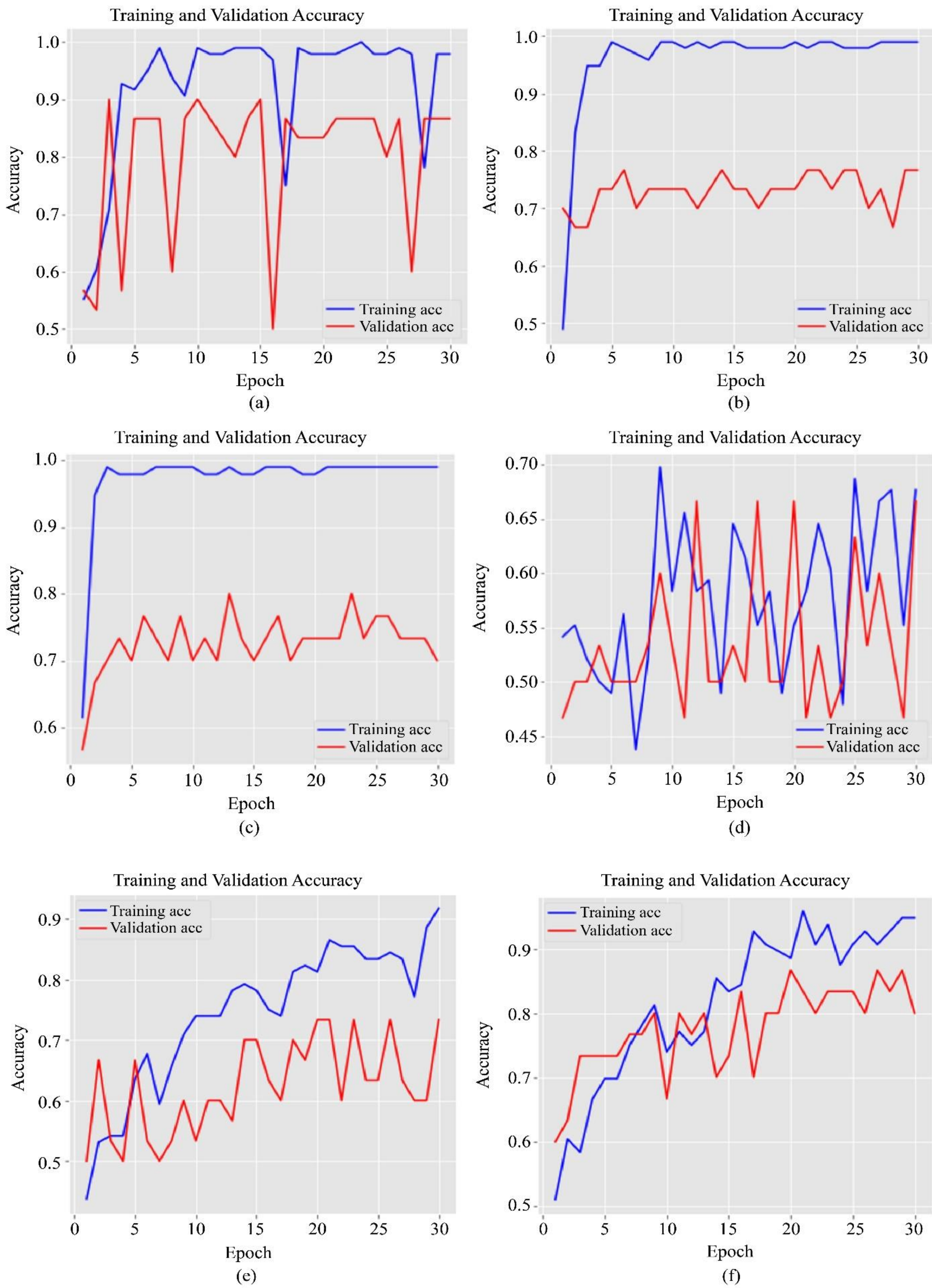


Fig. 3 Training and validation accuracy of six pre-trained Models (a) Densenet121, (b) Mobilenetv2, (c) Inceptionv3, (d) Resnet50, (e) Vgg19, and (f) Vgg16 on original images with normalization

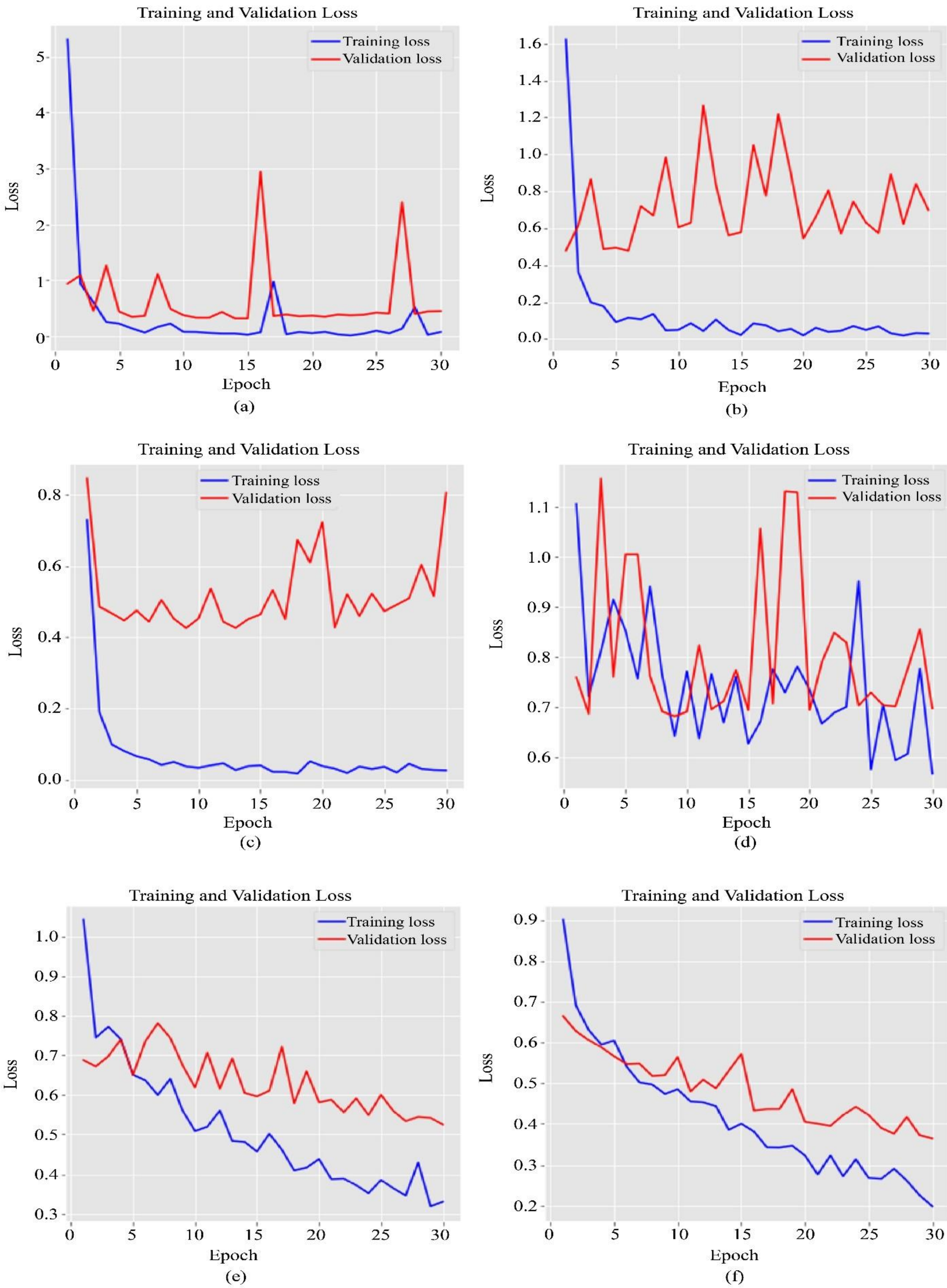


Fig. 4 Training and validation loss of six pre-trained Models (a) Densenet121, (b) Mobilenetv2, (c) Inceptionv3, (d) Resnet50, (e) Vgg19, and (f) Vgg16 on original images with normalization

Both vgg19 and vgg16 attained a testing accuracy of 70%. Similar to validation accuracy, the ELDCNN model and six pre-trained models' testing accuracy range is minimal due to the limited dataset. The performance comparison of ELDCNN and six pre-trained models on original images with normalization during testing is shown in Figure 6.

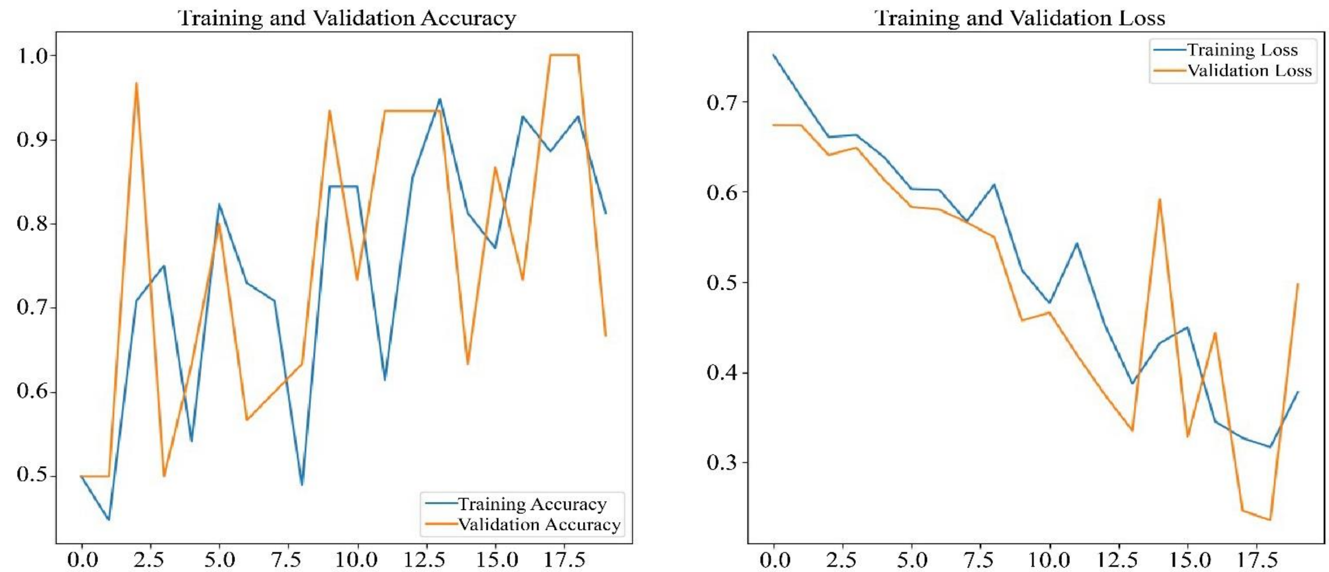


Fig. 5 ELDCNN accuracy and loss on original images with normalization

Table 5. Test results of the ELDCNN model and six pre-trained models on original images with normalization

Algorithms	Accuracy	Precision	Recall	F1-score
ELDCNN	87	100	75	85
Densenet121	87	90	83	80
Mobilenetv2	74	71	83	76
Inceptionv3	79	81	75	78
Resnet50	75	68	91	78
Vgg19	70	66	83	74
Vgg16	70	69	75	72

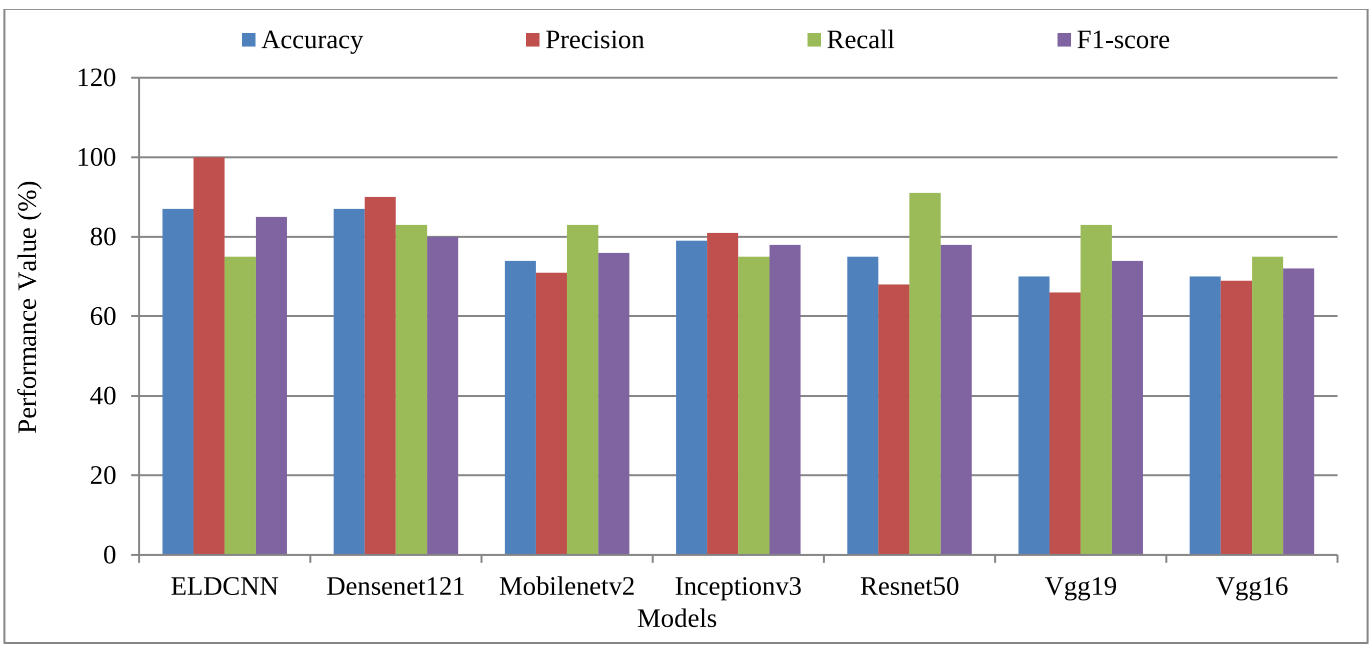


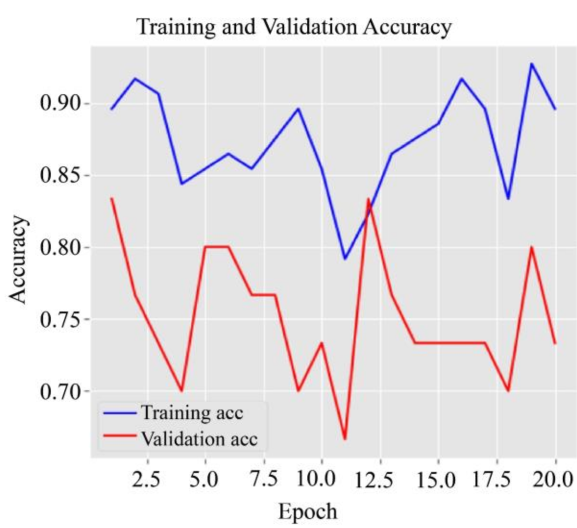
Fig. 6 Performance comparison of models when tested on original images with normalization

The finding shows that the basic normalization alone does not add enough variance to the data. Because of this, ELDCNN and six pre-trained models trained with normalization do not handle new or different data either. This may cause problems with images that differ from those seen during training, resulting in lower performance. This problem is reflected in testing metrics, where accuracy and other measures are not reaching their optimal levels.

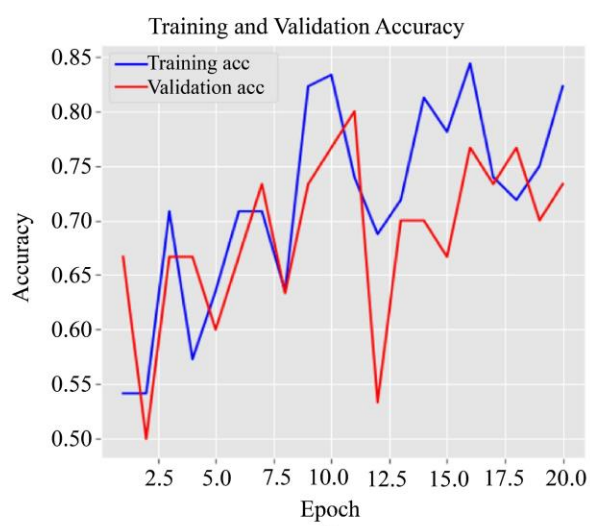
5.2. Performance of ELDCNN and Pre-trained Models on Augmented Original Images

Figure 7 illustrates the accuracies achieved in both the training and validation phases of the six pre-trained models on augmented original images. Following augmentation, both training and validation accuracy have improved compared to models trained on original data. Augmentation helps to enrich the training dataset, enabling the models to learn more effectively about the various characteristics present in the data. This prevents the model from memorizing the training data and improves its ability to perform best on new data. Training and validation loss of six pre-trained models on augmented original images are given in Figure 8. The lower training and validation loss indicates better convergence and reduced risk of overfitting.

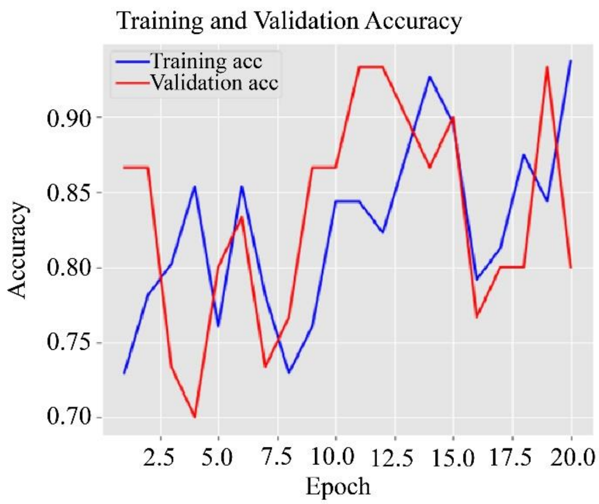
Assessment of ELDCNN model accuracy and loss during training and validation with augmented original images are shown in Figure 9. ELDCNN utilization of data augmentation led to the best performance across all metrics compared to the six pre-trained models. Augmentation addresses the insufficient variations by increasing the dataset. With augmentation, ELDCNN performed well because they can handle patterns and a wide range of image variations well. The performance comparison of ELDCNN and six pre-trained models on augmented original images during testing is displayed in Figure 10. The results achieved after testing the models on augmented original images are stated in Table 6; the ELDCNN model has an accuracy of 95%, which follows precision, recall, and the f1-scores of 92%, 100%, and 96%, respectively. Compared to the test accuracy of the ELDCNN model obtained using original images with normalization, the test accuracy of the ELDCNN model with data augmentation is improved by 8% in this study. The results also indicate that the augmentation has slightly increased the pre-trained model's test accuracy. The densenet121 achieved 88% test accuracy, which exceeds the accuracy of mobilenetv2, inceptionv3, resnet50, vgg19 and vgg16 models. The densenet121 test accuracy is 1% better than the densenet121 model and ELDCNN model test performance on original images with normalization. After densenet121, inceptionv3, mobilenetv2 and vgg16 scored well. The inceptionv3 model accuracy is 80%. Next, mobilenetv2 obtained 79% accuracy. The obtained accuracy is 5% higher than the mobilenetv2 test accuracy on original images with normalization. However, resnet50 accuracy is lower compared to its test accuracy on original normalized images. The vgg16 achieved an accuracy of 79%, which is 9% higher than the accuracy of vgg16 obtained during testing original images with normalization. The vgg19's test accuracy is 5% higher than the same model findings derived from testing original images with normalization. Additionally, the accuracy of ELDCNN with data augmentation is 7% better than the densenet121 with data augmentation. In normalization, the models lose the variety of data and perform poorly throughout the training, validation and testing. Augmentation resolves this by creating more data samples. The proposed ELDCNN model accuracy is improved through data augmentation, and it performs better when classifying soil types than ELDCNN on original images with normalization. Also, six pre-trained models were used on original images with normalization and augmentation. These findings indicate that, among the models tested, the proposed ELDCNN model with data augmentation achieved the highest accuracy. This highlights its effectiveness in accurate soil type classification.



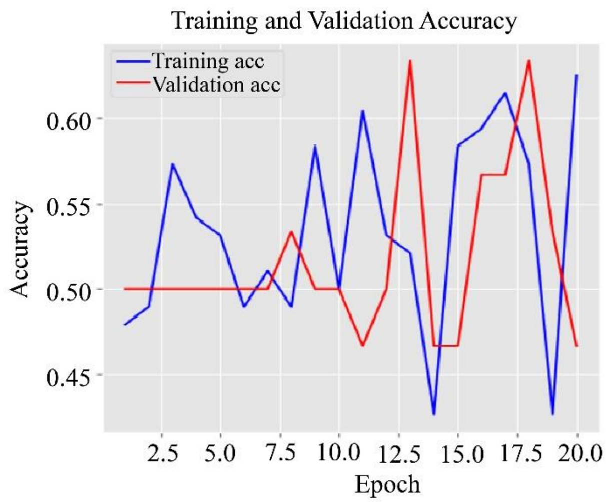
(a)



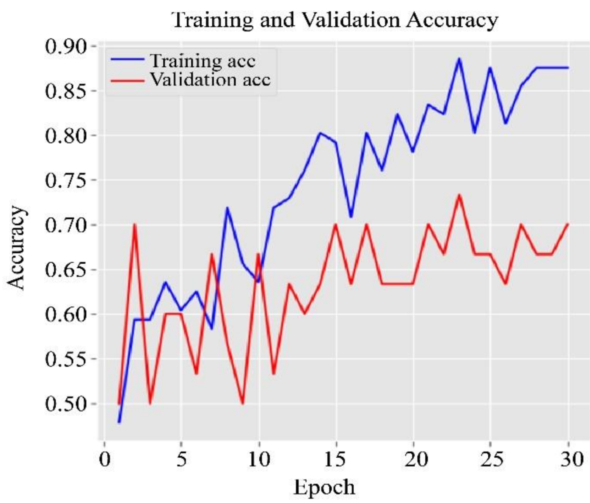
(b)



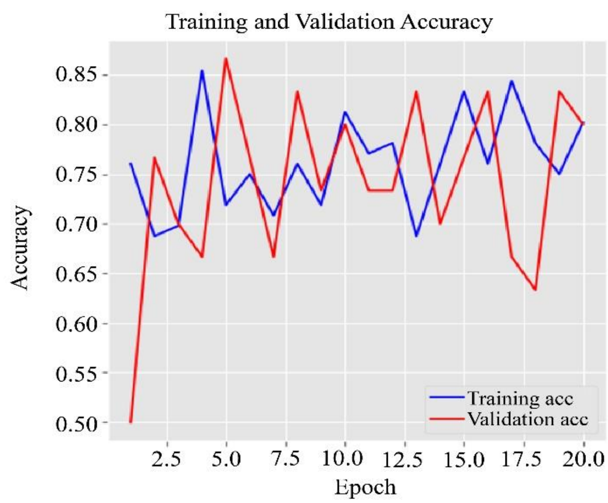
(c)



(d)

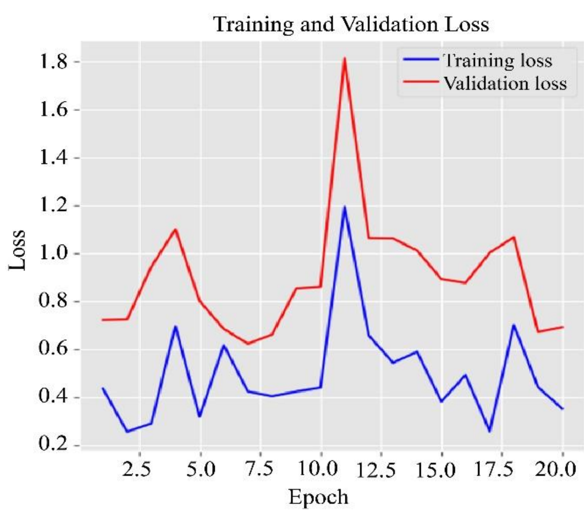


(c)

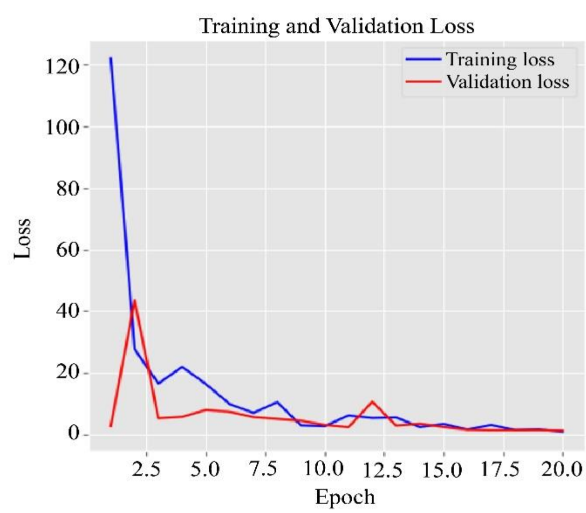


(d)

Fig. 7 Training and validation accuracy of six pre-trained Models, (a) Densenet121, (b) Mobilenetv2, (c) Inceptionv3, (d) Resnet50, (e) Vgg19, and (f) Vgg16 on augmented original images.



(a)



(b)

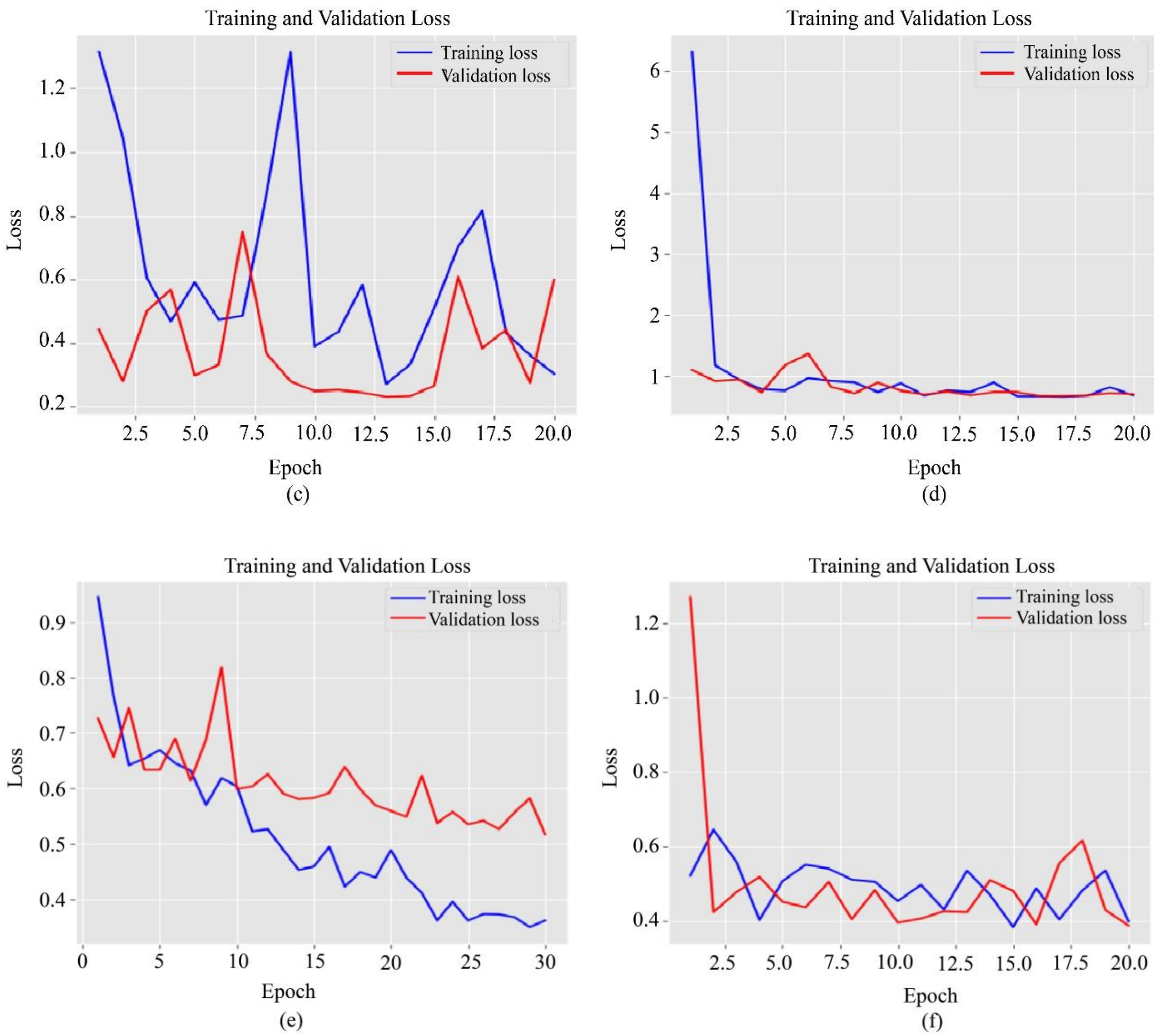


Fig. 8 Training and validation loss of six pre-trained models, (a) Densenet121, (b) Mobilenetv2, (c) Inceptionv3, (d) Resnet50, (e) Vgg19, and (f) Vgg16 on augmented original images

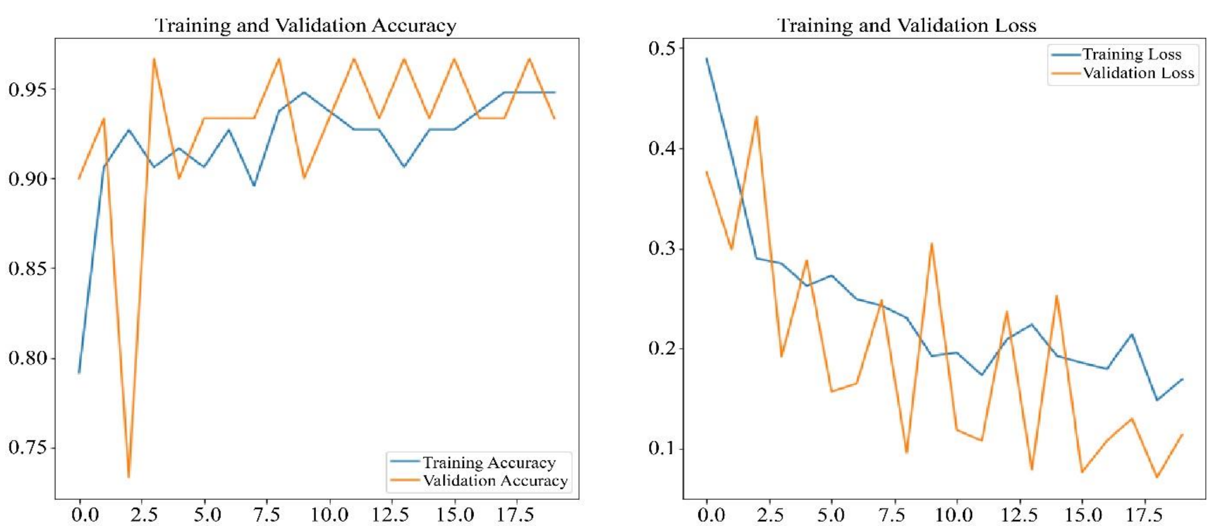


Fig. 9 ELDCNN Accuracy and loss on augmented original images

Table 6. Test results of the ELDCNN model and six pre-trained models on augmented original images

Algorithms	Accuracy	Precision	Recall	F1-Score
ELDCNN	95	92	100	96
Densenet121	88	90	83	87
Mobilenetv2	79	53	100	82
Inceptionv3	80	77	83	80
Resnet50	66	60	100	75
Vgg19	75	68	91	78
Vgg16	79	76	83	80

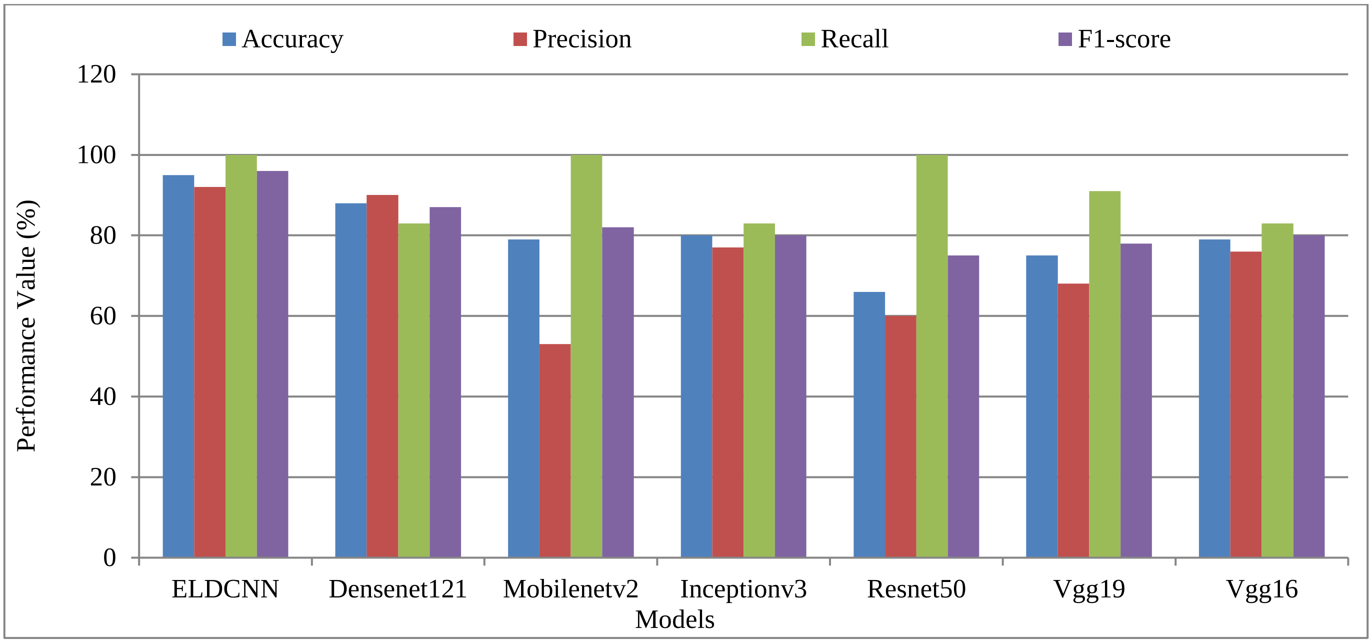


Fig. 10 Performance comparison of models during testing with augmented original images

6. Conclusion and Future Work

Soil is indispensable for agriculture. The lack of suitable soil in a particular location will affect plant growth. The soil varies from region to region because of climate and soil forming process. Understanding the different soil types is necessary because they are important to agriculture. The study of soil classification is a growing research area. It is a complex task that requires fundamental soil knowledge. Various studies have suggested many techniques, but classifying soil types remains time-consuming and less effective. As a result, this research investigates the accuracy improvement using the proposed ELDCNN model for soil type classification, with six pre-trained models used for comparison. In the beginning, 150 soil images with normalization are categorized using the ELDCNN model and six pre-trained models. The normalization limits both the model's experience with different types of data. A broad data range is required for effective findings; thus, augmentation techniques are applied to original images and their impacts are examined. The ELDCNN model with augmentation has a testing accuracy of 95%. It is 8% higher than the ELDCNN test accuracy on original images with normalization. Furthermore, compared to mobilenetv2, inceptionv3, resnet50, vgg19 and vgg16, the densenet121 model test accuracy is 88% after augmentation. The study findings indicate that augmentation techniques are effective and improve test accuracy. The proposed ELDCNN with augmentation has produced good results; therefore, it is ideal for soil type classification. This research improves crop production by helping the Tiruppur district of Tamilnadu, India; farmers make appropriate decisions before planting the crops in suitable soil. Future work is to add more soil types to expand the application area of the developed models.

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