Soil texture prediction using machine learning approach for sustainable soil health management

ABSTRACT

Soil in the earth acts as a foothold for all crops. Soil texture is the most important soil health indicator being used for the selection of crops, mechanical manipulation, irrigation management, and fertilizer management. The texture of the soil influences the storage and flow of air and water within the soil, as well as root development, the accessibility of plant nutrients, and the activities of different microorganisms. These factors collectively impact the soil's fertility, quality, and soil health. A conventional method of soil texture analysis is cumbersome, time-consuming, and labor-intensive. Machine learning (ML) is a newly emerging technique being used to assess the soil's physical, chemical, and biological properties quickly in real-time. This is an eco-friendly approach since it does not involve any hazardous chemicals. Machine learning can learn complex features and predict nonlinear properties. Convolutional Neural Networks (CNN) employs convolutional layers to automatically learn features from the input data and is widely used in image classification, object detection, and image generation tasks in a short time. Soil texture images are given as input dataset after the image subsetting, data preprocessing, and Image augmentation. This gives a CNN-based soil texture predictive model with a reliable accuracy of 87.50% at a lower cost.

Keywords: Machine learning; Convolutional Neural Network; Soil texture prediction; Soil management.

1. INTRODUCTION

Agriculture stands as a pivotal component within India's economy, engaging a considerable segment of its populace. It holds the capacity to impact the nation's Gross Domestic Product (GDP) while also serving as a principal source of livelihood for a substantial proportion of the workforce. In rural areas, the agriculture sector assumes the role of a primary income generator. As per the National Sample Survey, approximately 70% of India's rural population relies on agriculture to secure their means of sustenance. The integration of contemporary advancements in precision agricultural methods and sensor technology has led to the establishment of lucrative agricultural operations [1]. Soil texture is an important soil physical property being used as a soil health indicator for sustainable crop production. Soil texture is the relative proportion of the sizes of soil particles, such as sand, silt, and clay. Soil texture is defined as the particle size distribution of the finer earth fraction (<2mm fraction). Sand and silt have their subclasses [2]. Sand can be classified as extremely coarse sand, coarse sand, medium sand, fine sand, or very fine sand [3]. This particle size distribution of soil plays a major role in water holding capacity, suitable crop cultivation, root penetration, preparatory tillage, irrigation scheduling, cropping system, soil erosion, fertilizer application rates, and frequency [25]. A better understanding of soil texture paves the way for implementing sustainable crop management practices. Soil texture is traditionally determined in the field using the feel method and then confirmed in the laboratory using the international pipette method [4] or the hydrometer method on particle size fractions (sand, silt, and clay). Traditional mechanical approaches utilized for soil texture analysis involve a multitude of intricate procedures, including drying, crushing, and sieving [5]. Among the mechanical methods, hydrometers and pipettes find extensive application [6]. In the laboratory, standard soil textural examination entails time-consuming techniques such as drying, grinding, and screening before sedimentation analysis of sand, silt, and clay using a hydrometer or pipette [7]. While this method produces accurate soil textural results, it is not intended for quick and high-density textural evaluation for geographic variability analysis. Furthermore, these procedures necessitate the use of H_2O_2, a corrosive reagent, to degrade the native soil organic matter (SOM). Machine learning offers a clear edge over conventional approaches when it comes to predicting complex soil properties [26]. Artificial neural networking, also known as neural networks or deep learning, is a subfield of artificial intelligence (AI) that seeks to simulate the functioning of the human brain. ANNs use radial basis function networks, perceptron algorithms, and backpropagation to build predictive models [8]. Its multi-layered neural architectures possess the innate ability to autonomously comprehend intricate spatial and temporal patterns present in intricate soil data, effectively overcoming the constraints of conventional methods. CNNs are specialized neural networks designed for processing grid-like data, such as images or time series. CNN was developed in the 1980s and requires a huge amount of training data as well as a high degree of computing resources [9]. They employ convolutional layers to automatically learn features from the input data and are widely used in image classification, object detection, and image generation tasks. CNN algorithms have shown extraordinary ability in analyzing complicated information, recognizing nuanced patterns, and generating predictions according to intricate data linkages. The convolutional neural network (CNN) stands as a potent technique widely employed in image processing and the detection of objects [10,22]. Deep learning has achieved remarkable success in various domains, including computer vision, digital soil mapping, soil texture prediction, and heavy metal prediction.

1.1. Advantages of machine learning

Enhanced Data Analysis: Machine learning techniques facilitate the efficient analysis of expansive and intricate soil datasets, unearthing concealed patterns and insights that may pose difficulties to discern manually.

Predictive Modeling: ML empowers the construction of predictive models that address diverse soil properties and behaviors, aiding in informed decision-making concerning agricultural and environmental practices.

Feature Extraction: ML algorithms possess the capability to autonomously identify pertinent features from soil data, diminishing the necessity for domain experts to manually curate or engineer features.

Tailored Recommendations: ML models can craft personalized recommendations tailored to soil management practices, encompassing optimal irrigation schedules, fertilization approaches, and crop selections.

Real-Time Environmental Monitoring: Machine learning expedites real-time monitoring of shifts in soil conditions, contributing to enhanced comprehension and effective management of soil health.

Eco-Friendly Applications: ML-driven analyses often eliminate the demand for destructive sampling or hazardous chemicals, aligning harmoniously with eco-conscious principles.

Integration of Diverse Data Sources: ML proficiently integrates a spectrum of data sources like satellite imagery, weather data, and remote sensing, culminating in comprehensive insights into soil dynamics.

Streamlining Repetitive Tasks: Routine tasks such as data cleansing, preprocessing, and quality assessment can be streamlined through ML automation, resulting in time savings and reduced errors.

1.2. Disadvantages of Machine Learning

Dependency on Quality Data: Machine learning models heavily rely on substantial and high-quality data for effective training, and sourcing such data can be particularly challenging for rare soil conditions.

Model Complexity: Advanced ML techniques like deep learning can exact significant computational resources and time commitments for training and operational deployment.

Risk of Overfitting: Elaborate models may excessively fit the training data, yielding suboptimal generalization to novel, unseen data. The implementation of regularization methods is imperative to mitigate this concern.

Interpretability Challenges: Certain ML models, particularly intricate neural networks, may pose interpretability challenges, complicating the understanding of the underlying rationales for model predictions.

Synergy of Expertise and Collaboration: Successful integration of ML in soil science necessitates collaboration between ML experts and domain specialists to ensure meaningful, accurate outcomes.

Model Generalization: Models tailored to specific geographic regions or soil types may exhibit limitations in generalizing effectively to dissimilar regions, warranting adaptation or retraining.

Ethical Considerations: Ethical alignment is crucial in ML-powered decisions and recommendations, particularly when influencing agricultural and environmental practices

Optimization of Hyperparameters: Achieving optimal model performance through hyperparameter tuning demands expertise and meticulous experimentation.

In summation, machine learning harbors a wealth of advantages for propelling soil science research and applications. Nonetheless, prudent evaluation of data quality, model selection, interpretative challenges, and domain knowledge is pivotal to extracting the full benefits while proactively addressing potential limitations.

2. MATERIAL AND METHODS

Soil samples were collected from the twenty villages of Madurai district. In total, 20 soil samples having different soil textures were collected by the feel method. The collected soil samples are processed, labeled, and stored in a poly container. Soil texture was determined using the International pipette method [7]. Based on the soil texture results from the international pipette method in terms of Sand, Silt, and Clay percentages together constitute the real texture of the soil when fitted in a soil textural triangle. That laboratory-assessed Soil texture data is used to train and test the developed CNN model.

2.1.CNN Methodology

The proposed methodology of this research study has a Convolutional neural network (CNN) to predict the soil texture by classifying the soil which takes soil images as input. The currently employed machine learning models for classifying the soil type were compared to CNN. Convolutional neural networks (CNN or ConvNet) are a subclass of neural networks that are mostly employed in voice and image recognition applications. With no loss of information, its integrated convolutional layer lowers the high dimensionality of images. CNNs are therefore very well suited for this soil texture prediction. CNN models were developed to classify soil texture using soil images [24]. This model utilized a Convolutional Neural Network (CNN) architecture, a pre-trained model capable of classifying images into 1100 different object classes. The significance of CNN-based deep learning models in this context was highlighted by [11].

2.1.1. Image acquisition

The images of soil samples were captured using a Samsung Galaxy M33 smartphone equipped with a high-resolution 50-megapixel camera. These images were taken from various angles against a white background at the Department of Soils and Environment, Agricultural College and Research Institute, Madurai, between 9:00 a.m. and 11:30 a.m. under sunlight and shade conditions. Research centered around identifying soil images using smartphones has explored a variety of approaches, including soil profiles [12] and the utilization of digital RGB photography combined with neural network models [13]. In the context of Convolutional Neural Network (CNN) prediction, "sub-setting images" involve the process of carefully choosing specific localized portions within an image to thoroughly analyze and predict outcomes. This technique is frequently employed to detect Regions of Interest (ROIs) encompassing the target object or feature that requires identification. Concentrating on these ROIs enhances CNN's predictive precision and operational efficiency. Feature extraction represents a vital phase in the utilization of computer vision methodologies to scrutinize and differentiate among diverse soil textures. This procedure encompasses capturing unique visual patterns capable of discerning varying soil textures based on the proportions of sand, silt, and clay particles present in the soil. Diverse methods are employed to quantitatively define these textural characteristics and distinguish between different soil textures.

2.1.2. Dataset Pre-Processing

The photographs that are taken from the dataset are of different shapes and sizes so they must be suitably resized and modified to meet the requirements before being fed into the model. Every image with colorfulness contains a color format of RGB in which it obtains three channels—each of them has three colors—Red, Green, and Blue—and must be read by the process for each use case. To enable the model to successfully process the data, the images are then turned into numerical arrays. The dataset may contain unclean data, hence preprocessing is required to clean the data. A substantial 60% of machine learning projects' effort should be dedicated to data preparation, underscoring its substantial influence on project outcomes [14]. Transforming raw data into a suitable format for machine learning is instrumental in shaping the quality and quantity of insights derived during training procedures.

2.1.3. Image augmentation

Image augmentation, a well-utilized strategy in Convolutional Neural Network (CNN) prediction tasks, holds particular relevance within the realm of computer vision. Its objective is to amplify the diversity of the dataset by subjecting original images to various transformations. The aim is to introduce variations without altering the core content or labeling of the images, mirroring real-world scenarios encompassing diverse lighting conditions, rotations, scaling, and other influencing factors.

Flipping: This technique entails horizontally or vertically flipping images to simulate different orientations.

Rotation: Images are rotated by specified angles to emulate changes in viewpoint.

Scaling: Images are resized to different dimensions, mimicking objects at varying distances.

Translation: Images are shifted in different directions to replicate slight positional changes.

Shearing: Introducing skew along the x or y-axis imparts a deformation effect.

Zooming: Images are expanded or compressed to represent a range of scales.

Brightness and Contrast Adjustment: Modifying brightness and contrast accommodates distinct lighting conditions.

Noise Addition: Introducing random noise imitates real-world noisy scenarios.

Color Shifting: Adjusting color balance, saturation, and hue accommodates diverse color variations.

2.1.4. Standardization of images

Image standardization involves preprocessing and scaling photographs using a standardized method to ensure uniform dimensions in terms of height and width. Following this rescaling process, the data exhibit a mean of 0 and a standard deviation of 1 (unit variance). This standardization process contributes to enhancing the quality and consistency of the data.

2.1.5. Convolutional Layer :

The convolutional layer comprises multiple channels, each containing learnable parameters or filters. The CNN network comprises four convolutional layers, each with a max-pooling layer, and was created to predict clay [15]. Building of multivariate statistical models combining photographs of soil samples to their known particle size distribution, seven image-processed data matrices (RGB, HSV, Grayscale, RGB + HSV, RGB + Grayscale, HSV + Grayscale, and RGB + HSV + Grayscale) were used (Fig. 1). These filters, with dimensions and weights smaller than the input volume, produce activation images by convolving each channel with input segments. Essentially, each filter traverses the input's height and width, performing dot product computations at localized positions. The output segment of the convolutional layer is generated by aggregating activation images from all channels. These channels can be applied to a single image or separate feature images within a CNN. Notably, the convolutional layer's parameters, including filter size and channel count, are crucial user-defined aspects of the network. Image classification follows five steps: convolution, activation, pooling, flattening, and dense. The convolution layer of 3x3 is built alongside 32 convolutional channels (filters). An image's pixels are input individually into the network for processing. Hence, for a 200x200x3 image, we need to feed 200 * 200 * 3 = 120,000 input neurons (i.e. 200 pixels on 200 pixels with 3 color channels, e.g. red, green, and blue). Thus, each matrix has a dimension of 200 by 200 pixels, totaling 200 * 200 entries. The matrix is then duplicated three times, with one copy for each of the colors red, blue, and green. A problem then occurs because each of the neurons in the first hidden layer would get 120,000 weights from the input layer. This suggests that the number of parameters would increase quickly as we add more neurons to the Hidden Layer.

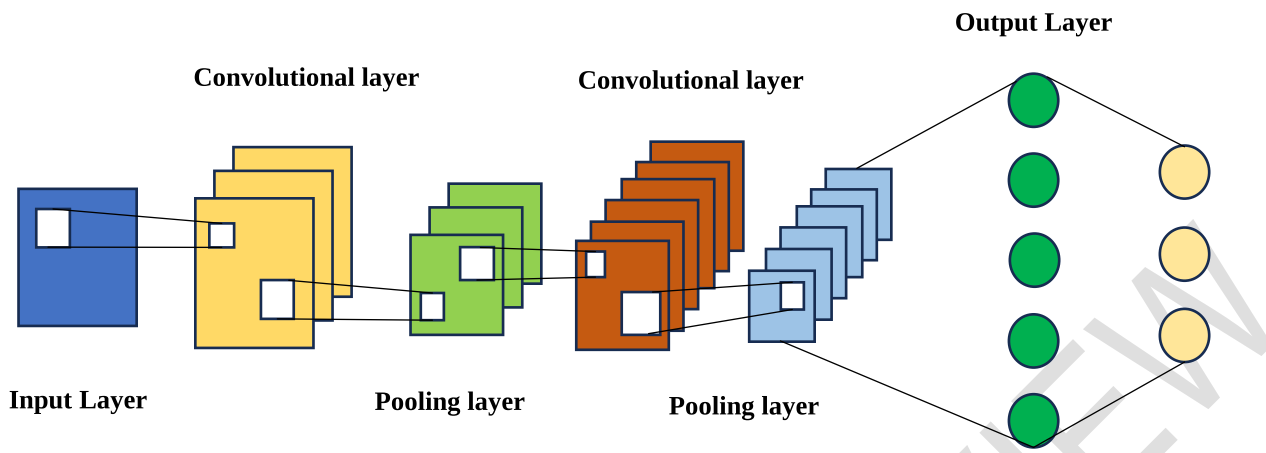

Figure 1: CNN Architecture

2.1.6. Pooling Layer:

Pooling, also referred to as subsampling, operates to reduce the resolution of features, bolstering their robustness against noise and distortions. This layer effectively achieves the down sampling of feature images by aggregating the proximal features. While convolution layers can accomplish down sampling through varying strides, a more potent strategy entails employing a pooling layer. Pooling essentially entails applying a filter to feature images, with the magnitude of the feature image being greater than that of the pooling activity. A common instance is the utilization of a 2×2 pixel pooling activity with 2-pixel strides. This approach consistently reduces the feature image's size by a factor of 2. Consequently, the dimensions are divided, resulting in a quarter-sized reduction in pixel quantity or value within every feature image.

2.1.7. Maximum Pooling (or Max Pooling):

Maximum pooling, a specific pooling operation, selects the maximum element within a region of the feature soil texture image delineated by the filter. This type of pooling emphasizes the most prominent feature within the soil texture image. Maximum pooling contributes to reduced computational demands by curtailing the number of learnable parameters. Additionally, it imparts vital invariance to inner representations. (Fig. 2)

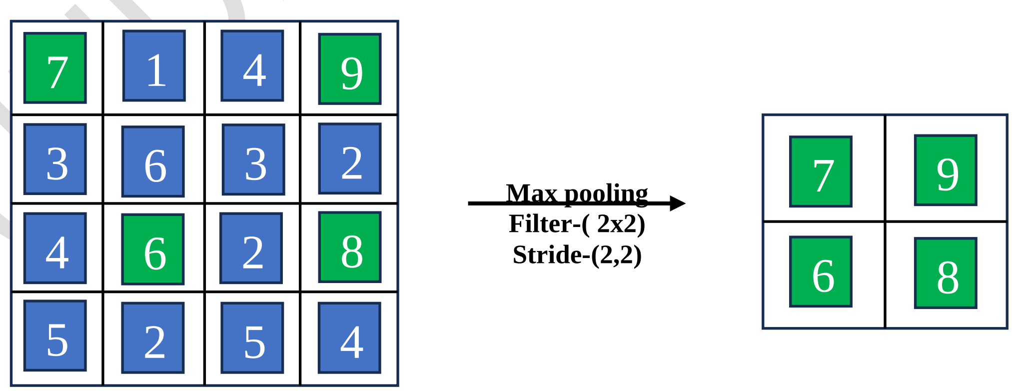

Figure 2: Max pooling

2.1.8. Activation function

Activation functions are mathematical expressions that determine the outcome of a neural system. These functions are integrated into each neuron within the network and make decisions regarding their activation or deactivation, based on the relevance of the input data for the model's predictions. Furthermore, activation functions aid in standardizing the output of each neuron within a range spanning from 0 to 1 or from -1 to 1. In neural networks, nonlinear activation functions are increasingly employed, enabling the network to comprehend intricate data patterns, conduct complex computations, and provide precise predictions. Among these functions, the Rectified Linear Unit (ReLU) function holds prominence, particularly in computer vision tasks. ReLU's widespread adoption stems from its efficient computational speed and its effectiveness in mitigating vanishing gradient issues[16]. Specifically, ReLU stands for the "rectified linear unit," constituting a category of activation function. Mathematically, it can be expressed as $y = \max(0, x)$.(Fig. 3)

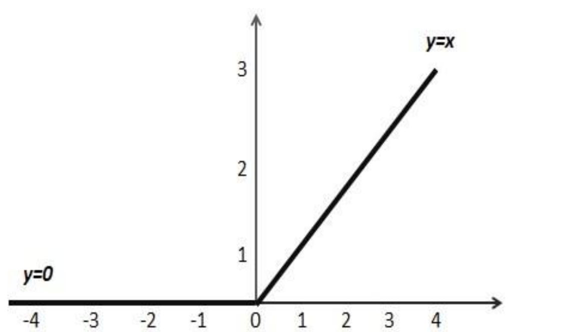

Figure 3: Rectified linear unit (ReLU activation function)

2.1.9. Fully Connected Layer:

Fully connected layers frequently find application as the concluding layers within a neural network(Tab. 1). In the context of a Convolutional Neural Network (CNN), the fully connected layer computes a comprehensive amalgamation of the preceding CNN model's weights, determining a specific target output outcome. This encapsulates the precise combination of elements. When fully connected layers are introduced, each component of a substantial number of extracted features from the previous layer becomes incorporated in the calculation of the output feature for each component. Among prominent AI models, certain final layers comprise fully connected layers that amalgamate the insights extracted by previous layers to compose the ultimate output. This layer stands as the second most labor-intensive stage subsequent to the convolution layer.

Table 1. CNN layer-wise architecture of data

Layers	Parameters Description
Input	JPEG, GIF, and other image files are expressed in an RGB format that may be represented as a 3D matrix.

Conv(a,b,c, d,e,f,g,h)	a=amount of anticipated input channels in the displayed picture (3 for RGB) b=number of output channels following the CONV phase. c=The convolution's kernel size d=The convolution kernel height e=The convolution's step (stride) in the width dimension f=The convolution in the height dimension's step (stride) g=The input plane data have additional zeros added to them on either side of the width axis. h=The input plane data have additional zeros added on either side of the height axis.
ReLU(a)	If the input is less than 0, the output of a rectified linear unit (activation function) is 0, else the output is raw. Is it True or False?
MaxPooling (a,b,c,d)	an AaB window-based max-pooling process that determines the maximum via ZaU stride length. a=The pooling filter's width b=The pooling filter height z=The pooling width step u=The height of the pooling stride
FullyConnected (a,b)	3*256*256 (3 color channels, 256 pixels high and 256 pixels wide) is an example of an input image size. b=Number of output classes smaller than the input image size.
Loss (a, b)	The predicted labels and the actual labels are input into the loss function, which then calculates a number to indicate how well the model performed. a=anticipated label b=real labels
Output	Analysis of patterns and classification (e.g. Image recognition)

2.2. Data splitting

After, processing of images, the dataset becomes primed for the application of machine learning algorithms. However, before selecting the appropriate training algorithm, it is recommended to partition the image data into three distinct segments: training data, validation data, and testing data. The sequence of operations involves initially training the artificial intelligence algorithm on the provided dataset, followed by validation and testing phases. Once testing is concluded, the resultant model is poised for deployment in real-world scenarios.

2.2.1. Training

In this study, the data was divided into 1100 images for training. The training process aimed to capture the dataset's complexities and attributes, mitigating challenges like underfitting and overfitting. Overfitting occurs when a model is too tailored to a limited dataset while underfitting results in a model that fails to capture the training data or generalize to new data. We have set training the model for 35 epochs, compiled with categorical cross entropy loss function and SGD (stochastic gradient optimizer) optimizer.

Training of model is performed on hp-laptop which have following hardware and software parameter.(Tab. 2)

Table 2. Software and Hardware Parameter

Name	parameter

PC-RAM	16GB
Processor	AMD Ryzen 5 7535U with Radeon Graphics - 2.90 GHz
Operating system	Windows 10 64 bits
Environment	Jupyter notebook
Language	Python

2.2.2. Testing Data:

The main role of a test dataset is to gauge how well a trained CNN can handle entirely new and unseen data. It serves as a simulation of real-world scenarios, ensuring that the model isn't merely memorizing the training data, but can make accurate predictions on unfamiliar instances. This portion of the original dataset is reserved for testing 77 images the trained model's hypotheses. Test datasets remain untapped until both the model and its hyperparameters are finalized. Subsequently, the trained model is evaluated against the test dataset to attain accurate metrics on its performance with real-world data.

3. HOW CNN ALGORITHM PREDICTING SOIL TEXTURE

In this research study, above mentioned image based soil texture prediction mechanism was developed using CNN algorithm. For training purposes, Images of soil texture were processed, features like color (RGB), and texture were extracted from all corners and edges of the images and the images were cropped and then augmented into multi-dimensions of more pictures. These processed images were given to the input neural layers for learning the intricate patterns of texture images, The initial layer captures the unimportant low-level features of the image but the maximum pooling of soil texture images reduces the spatial dimension of the input and focuses on the most important features of the region of soil texture image in order to retain the distinctive features of the image for soil texture prediction. These hidden layers of neurons process the soil textural images by learning the complex textural patterns and provide the results with reliable accuracy of prediction as the output layer.

4. RESULTS AND DISCUSSION

Stoke's law was employed to establish the connection between soil texture and the proportions of sand, silt, and clay. The categorization of the soil was carried out using the USDA soil taxonomy system[17]. The suggested real-time classification method for different soil types is based on the convolutional neural network. The deep-learning-based approach can quickly and accurately identify the different types of soil from soil photographs by automatically extracting their discriminative features. The impact of mineral color on the HSV parameters examined in this study is rooted in the observation that sand particles tend to exhibit a brighter appearance under LED illumination within the dark chamber, a phenomenon highlighted in previous research [18]. A total of 20 soil samples from the three ecoregions surrounding the Agricultural College in Madurai were taken at random to account for site accessibility. These samples added up to more than 1100 pictures, which the model was then given. The Python IDLE software's creation and application of this model yielded the results shown below. (Tab. 3)

Table 3. Describes the process of epochs and calculation results of accuracy and loss

Prediction of Sandy soil texture		
Epoch	**Loss**	**Accuracy**
1	0.3965	0.8125
2	0.4209	0.8438

3	0.4308	0.8672
4	0.4267	0.8687
5	0.3844	0.8750
6	0.4360	0.8594

Epoch is a specific hyperparameter that dictates the frequency with which the learning algorithm assesses the complete training dataset. A single epoch signifies that the entire dataset has been processed through the learning process of the CNN model only once. Subsequently, the model's learning persists, contributing to the enhancement of its accuracy by gaining further insights from the dataset. Training is fixed with a sufficient number of epochs as 35 epochs. Model training was stopped early at 5 epochs because the performance of training started to degrade after epochs 5 or epoch 6 onwards(Tab 4).

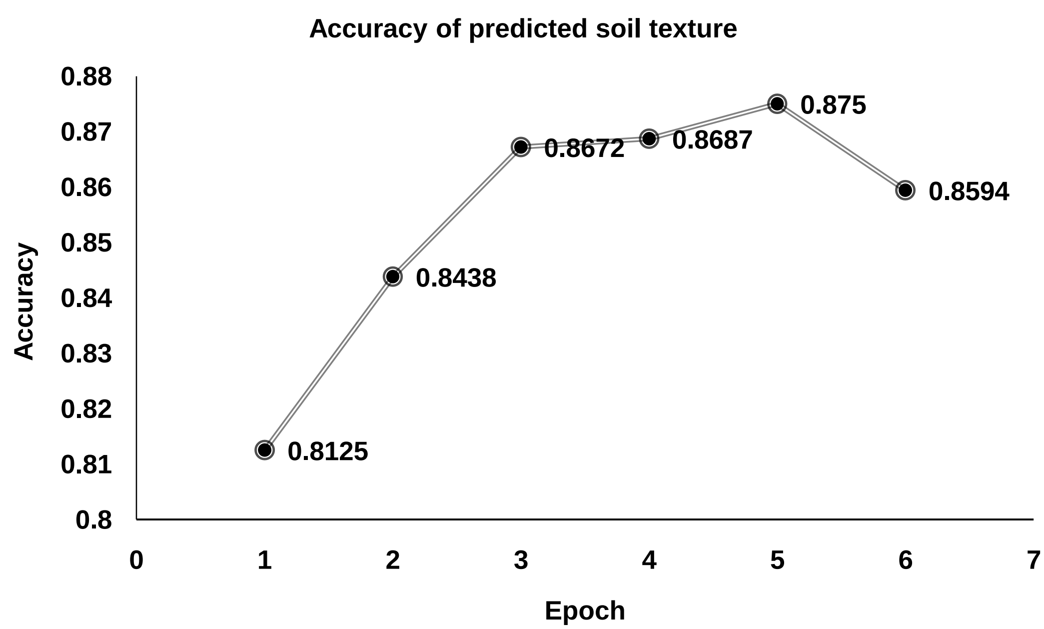

Figure 4. The trend of predicted accuracy

Accuracy serves as an assessment of the model's overall effectiveness across various classes, proving valuable when each class holds equal significance. This metric is derived by dividing the total correct predictions by the total predictions made. Throughout each epoch, it is imperative for the model's accuracy to progressively increase. As the epoch increases, accuracy increases up to a certain number and then decreases due to the overfitting problem(Fig. 4). Data augmentation improves the accuracy by increasing the number of images for the learning process. Within each epoch, the learning model initially acquaints itself with the dataset using an algorithm. Subsequently, the acquired knowledge is employed within the same algorithm, enabling the model to refine its understanding of the dataset and thereby achieve heightened accuracy. The proposed CNN-based model predicted the sandy soil with the highest accuracy of 87.50% at the 5th epoch. The higher accuracy for predicting sandy texture is due to image-extracted features like color, particle, and texture [19] from Figure 4. The higher accuracy of sand prediction is due to the HSV feature extraction of soil texture images [23]. The trend of accuracy in soil texture prediction increases up to a certain level of epoch 5 and then decreases may be due to an overfitting problem. The role of the loss function is to measure the disparity between the anticipated and predicted values. It assesses how well the neural network's representation of the training dataset aligns with reality. During the model training process, the objective is to minimize this divergence in loss between the predicted outcomes and the desired targets. The minimum loss was found to be 0.3844. The lowest accuracy of 81.25% was recorded at one epoch. The reason for the lower accuracy may be due to the lower number of samples [20]. The experiment results demonstrated that the approach had an 87.50% success rate in correctly classifying the soil picture. The improved performance of CNN arises from its capability to perceive the image on a deeper level, effectively interpreting it as a composition of diverse edges, lines, and corners. This enables the CNN to effectively capture the content within the image[21].

4. CONCLUSION

Soil is a highly heterogeneous natural resource that provides food and nutrition for the global population. Machine learning-based CNN models can learn complex features like soil texture and predict it with reliable accuracy in a short time. Manual estimation of soil texture has poor accuracy and laboratory methods are time-consuming as well as tedious process. In this study, we used the CNN approach to predict soil texture under a Python environment. The soil texture image consists of 1100 images and 77 images for training and testing data sets used for soil texture prediction modeling. Based on these results, it was concluded that a CNN is a good soil texture predictive model and it predicts soil texture with a higher accuracy of 87.50% at low cost. More research is warranted to predict soil moisture along with texture using large data sets in real-time for precise prediction of soil texture for sustainable soil health and crop management [27].

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