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Soil Classification Using Machine Learning

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Abstract: A topic that evokes a large base for assorted studies, across numerous countries is soil classification. Recently, the world recorded an exorbitant rise in human population, the denouement is a higher demand for food and shelter. Both these factors directly demand exceptional study in geo technology, if not, a more reliable and faster method to do so. Conventional strategies taken by farmers are insufficient to meet the skyrocketing demands, and as a result, they must impede soil cultivation. This leads to the requirement to remain cognizant of the optimum soil type for a certain crop to maximize agricultural production. Several laboratory and field methods for classifying soil exist, however, these have constraints namely time and labour sine qua non. A need for a software-based soil categorization modus operandi that will assist humankind from a range of engineers to farmers, in reducing the time deviation is sought. This paper discusses apropos software, that allows soil classification to be achieved more efficiently. The functioning includes image processing and Computer vision-based soil classification methodologies, embodying the customary image assessing algorithms based on parameters, namely texture, colour, and particle size.

Keywords— *Soil, Classification, CNN, Machine Learning, Image Processing*

I. INTRODUCTION

A. History and leads

The world population is growing by the day, necessitating growth in the yielding food, clothes, and medicines on a similar tally to ensure their existence on this planet. Agriculture is the primary source that can meet expanding demand in this aspect. Soil is a fundamental agricultural tool since it contains nutrients integral to producing crops. Several classes of soil exist in each country, and variants could potentially originate around the globe. Many agricultural jobs and projects are evaluated contemporarily by the properties of the soil that affect agriculture engineering as a result. Knowing the properties of the soil might present pragmatic data to create a more rational and cautious management plan and employ them in agricultural regions. Profoundly, biota, geological history, and temperature are significant elements that have a notable impact on the soil's chemical and physical properties, whereas topography and human activity have a pivotal influence on soil characteristics at a local level. The distinct pieces (namely plant fragments, clay minerals, and quartz grains) that may be seen in disintegrated form using an optical microscope are the rudimentary elements of the soil. Soil structure is bound to the fineness, shape, contrast, frequency, size, voids, and the spatial arrangement of significant granules et al [1].

B. Objective of this research

The objective is to create an automated system that can accurately classify various types of soils based on their characteristics or attributes. This classification has applications in a variety of sectors, including agriculture, environmental science, geology, and civil engineering. The major goal is to create a model that can accurately classify various types of soils. The model should be able to recognise and differentiate between soil types based on their distinct characteristics, such as texture, composition, colour, moisture content, organic matter content, and other important factors. The combination of CNN and machine learning algorithms enables the processing and analysis of enormous datasets in an effective manner. The goal is to create a model that can swiftly analyse and classify soil samples, allowing for timely decision-making in a variety of applications et al Breul [2]. Manual labour and human skill are frequently used in traditional soil classification procedures, which can be time-consuming and subjective. The goal is to use machine learning techniques to automate the categorization process, lowering the requirement for manual labour and minimising human biases. The model built should be scalable and capable of processing heterogeneous soil datasets from various areas or countries. Even if the collection contains samples

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from previously unknown areas, it should be able to generalise well and reliably categorise soils. CNN models can learn to extract relevant features from raw soil data, improving the classification process's interpretability et al Brungard [3]. The goal is to uncover and comprehend the key elements that influence classification judgements, which can provide insights into the underlying qualities and characteristics of various soil types.

C. Arriving towards computer-driven methodologies

The soil texture and color can be determined using a variety of conventional methods, namely Pipette, elutriation, decantation, and Munsell color chart methods. There is also the USDA triangle technique for classifying soils. These procedures need a lot of work and time, which is a drawback. Hence, using computer vision and image processing-based approaches to categorize soil has struck a chord with researchers. The farmers in rural areas lack understanding or information on the soil's texture in relation to field research. They are farming without conducting adequate or sufficient testing beforehand, and they have no idea how to choose the right soil for the crops they intend to plant. This has an impact on the crops' general (overall) growth. Hence, to produce crops properly, farmers need be provided with a hassle-free solution that also informs them about the soil they are utilizing. Many computer-based methodologies and algorithms have been presented in recent years in addition to the conventional approaches. These techniques demand pictures of the soil to work with. To attain a decent yield, growers must be able to select the crop to produce depending on the nutrition of the soil besides the physical and environmental circumstances. Thus, deep learning algorithms are being used to analyses the soil and suggest appropriate crops in this regard to assist the former. The neural networks with representation learning are the foundation of deep learning technologies. Applications for data analysis and picture processing are applied with positive results. Deep learning has been effectively employed in a myriad of fields, including identification, entertainment, healthcare, fraud detection, gaming, language translations, etc. In the immediate present, deep learning has been used for several agricultural applications, with the greatest results et al [4]. The first step is picture processing and soil categorization based on computer vision. There are four main steps in it:

- Acquiring the images for dataset
- Segmentation of dataset
- Identification of major characteristics
- Classification of soil.

Utilizing a camera setup, a soil database is first built. Secondly, segmentation is used when it is necessary to divide the area of interest. Subsequently, different color and texture elements are derived. Using extracted characteristics, a pre-trained classifier like generates the ultimate identification results. The traditional digital photograph processing cycle for classifying soil is shown in Figure 1. On the contrary, deep learning has emerged as a generic approach to machine learning, which generates cutting-edge breakthroughs in many areas of photograph processing and computer vision research with the availability of enormous quantities of data. The optimum traits are those with strong categorization, highly precise, but also weak resistance [5]. The variety of characteristics that were chosen are lower than the initially set features. Colour, texture, and morphology are only a few of the characteristics that may be leveraged in the classification of soils, thus matrix factorization techniques can be employed in enhancing accuracy. Two classes of dimensionality reduction, subspace and feature selection, can be quickly distinguished. Principal component analysis (PCA), linear discriminant analysis (LDA), random projection, and other techniques are examples of subspace approaches. RP may be performed without any prior training, making it significantly quicker than PCA and LDA. Two-dimensional RP (2D-RP), two-directional two-dimensional RP ((2D)-2RP), and sparse RP [6] are a few variations of RP that have been advocated. These enhancements need much less computing variability and storage expense than conventional 1D- RP.

II. LITERATURE REVIEW

Zhang et al. [7] advocated a classification system that applies a wavelet transform approach to classify soil with variant textures. Wavelet transform, a strong photograph and signal analysis technique, due to its multi-resolution capabilities, is harnessed to extract features. The utility of ML parameters besides Fisher’s Linear Discrimination Analysis (FLDA) is also witnessed in the reduction of vector dimensions in characterization. An automated technique for classification was proposed by Zhang et al. [8] wielding wavelet-based statistical models and hyperspectral soil fingerprints. Two models, namely hidden Markov models and maximum-likelihood models, are used in the classification process. The HMM classifier in 3-class technique offers a precision of 89-95% for sand, silt, and sand dominant textures correspondingly. Using RGB form pictures,studied a technique for classifying soil texture. A soil texture classification technique involving mask convolution was put out by Shenbagavalli and Ramar [9]. Absolute mean, skewness, etc., of the soil picture, were computed to construct the feature vector for additional processing. A new classification method is constructed to employ data like hyperspectral soil textures that lay out rich intrinsic properties. A retrieval-based procedure, proposed by Shenbagavalli and Ramar will be discussed in depth in accordance with our dataset. A computer vision-based texture analysis on a picture was advocated by Sofou et al. [10]. Third order moment soil characterization approach based on textural characteristics was provided by Breul and Gourves [11] in the field. To extract textural aspects of pictures, S. Dewari et al. [12] advocated a soil classification approach employing the Gabor Filter, color quantization, and Low mask on the original soil images. O'Donnell et al [13].'s work was designed to establish a system for quantifying and classifying soil redoximorphic features (SRFs) from soil cores by employing photograph processing and classification methods on digital camera-generated pictures. Using DIP, Maniyath et al. [14] created a successful technique to identify soil color. Pictures are changed from RGB to HSV. This same system reported a prediction performance of 100%. To assess and evaluate the pH value of agricultural soil, Gurubasava and Mahantesh [15] advocated methodologies and techniques based on digital photograph processing. A deeper dive into soil composition and textural analysis in mineral differentia from identical fragments of the preliminary igneous, sedimentary, and metamorphic rock through heterogenous weathering architecture to the bifurcation of clay minerals, hydrous oxides, and organic matter of natural soil formation in the biosphere. This layer oif information was provided by Hsai Yang et al [16]. As we move further into the study, several algorithms based on traditional photograph processing and computer vision methods that have been advocated by V. Prabhavathi and P. Kuppusamy, et al [17] were implemented. Most agronomic models proposed by A. Priyadarshin et al [18] were built on neural networking which then utilizes ICRS to analyze and bifurcate into soil features. After doing so, we can smoothly move over to the estimation of soil moisture. The usage of the 2D-RP models has enhanced our understanding of our deep learning model as will be discussed in full depth later. The traditional image processing and classification allows us to glance at the impact on physical and chemical attributes of the dataset.

A. Contribution of this research

Despite contemporary attempts to classify soil, there are not any thorough literature evaluations or surveys on the topic of employing photograph processing, machine learning including deep learning techniques. In a handful of review publications, machine learning or deep learning-based methods have not been introduced, continuing to concentrate only on classic photograph processing and computer vision research. Albeit there was solely one survey that compared computer-based applications to conventional models. Less than 10% of the papers in a recently published revised review of machine learning in the administration of crops, water, soil, and animals were focused on soil management. Moreover, most of the agronomic models [19] were built on neural networks, incorporating deep learning. For said categorization of soil, researchers have presented an Intelligent Crop Recommendation System which takes environmental factors, soil nutrient levels, and soil features into account. These days, deep learning techniques are used to elegantly classify photographs. Within the purpose of estimating soil moisture using synthetic aperture radar data, a Complex Valued CNN (CV-CNN) was created. As a result, this work is devoted to a survey of the relevant literature, which ranges between traditional photograph processing to cutting-edge machine and deep learning techniques alongside a practical implementation of machine learning to encompass the same. The following are the research's primary recommendations:

- The major objective is on outlining a shared understanding of contemporary soil classification methods, which can aid future researchers in understanding the key concepts and developments in the machine and deep learning related geo-technological besides geoinformatics field.
- Numerous databases which include comparable besides assorted types of soil images that has been produced in various settings as required for their research.
- Set datasets include accuracy and precision up to 91%
- Assigning set datasets to the allocated information besides enforcing these to the database.

Important components of systems for classifying soil using deep learning and processing are also evaluated and explained. Although deep learning-based approaches for classifying soil typically perform better than traditional methods, they require a significant computing resource, including centralized processing units and graphics processing units.

III.METHODOLOGY

A. Convolutional Neural Network

A convolutional neural network, or CNN, is a genre of deep learning neural networking designed for analysing structured arrays of input. CNN regulates multitudinous conventional techniques include categorization of photographs and colossally brought to bear in computer vision. This multi-layered neural network consists of the stacking of various hidden layers on top of one another, sequentially, permitting the study of hierarchical features given their sequential construction. Convolutional layers are recurrently ensued by activation layers and some pooling layers, respectively. The early CNN LeNet-5, introduced by Yann LeCun in 1998, is a straightforward model that ameliorates comprehension of rudimental design ideas. It is employed to decipher handwritten scripts. Assimilating six layers, LeNet-5 can differentiate between minuscule handwritten numerals but not between, for instance, the 26 letters of the alphabet or, more specifically, faces or things. Even though preeminent advanced networks of today may surpass 30 layers, millions of parameters, and branching, the fundamental convolutional kernels stay the same [20].

B. Study of soil

Soil studies are conducted to assess statistics regarding its properties that directly influence numerous factors ranging from mapping to soil formation, fertility, chemical, physical, and biological characteristics besides the relationship between these characteristics and soil management, usage, and crop production.

1) **Size of soil particles and texture:** Solid soil constituents can divaricate in size from tiny boulders (>30) to colloidally dispersed mineral and organic particles (1 m). They may also differ in mineral differentia from identical fragments of the preliminary igneous, sedimentary, and metamorphic rock through heterogenous weathering architecture to the bifurcation of clay minerals, hydrous oxides, and organic matter of natural soil formation in the biosphere.

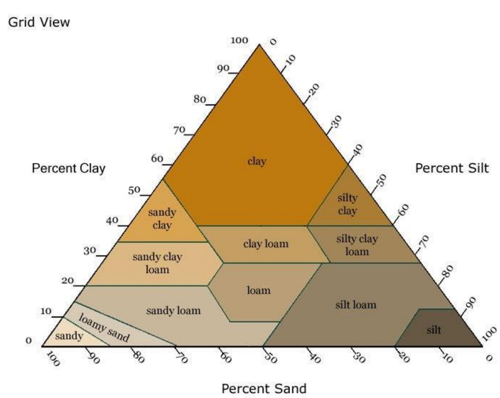

FIGURE 1. Agricultural textural classification chart

Classification is the process of arranging items into groups in a logical and sequential order as shown in Fig.1. It differs based on the forementioned characteristics to investigate and recognize them. The field method used by civil engineers for the identification of soil texture are as follows:

- Gravel: It can be simply defined as the loose aggregation of rock fragments. Due to its solid and strong texture and characteristics, it cannot be ribboned or casted.
- Sand: It consists of an unrefined appearance where the grains can be differentiated. It also has an extremely free flowing nature when at dry state.
- It cannot be ribboned.
- Upon air drying- It will not form a cast. Tends to fall apart with the release of pressure.
- When moist- A cast can be formed which crumbles when lightly touched.

2) **Silt:** It consists of a mixture of silt particles with minuscule amounts of sand and clay. With a tendency to be cloddy when dry, it easily pulverizes to a powder that has a soft flour-like texture.
   - It tends to ribbon with a broken appearance but feels smooth.
   - It forms a cast that can be handled without breaking when air dried.
   - The cast formed can be handled freely and when wet, it causes puddles.

3) ***Clay:*** They are the fine-textured soils that, when dried, crumble into highly solid lumps. It is incredibly difficult to grind into a fine powder resembling soft flour. The cohesive qualities of the damp soil serve as the basis for identification.
   - It forms a long, thin flexible ribbon due to its considerable plasticity.
   - It forms a cast that can be handled freely without breaking both when air dried and moist [21].

4) **Loam:** They are textured solid, with high quantities of humus and fertility which enables it to have better drainage and infiltration of water and air than silt- and clay-rich soils. It can be ribboned and casted due to its strong durability.

C. Purpose of soil classification:

The various motives of soil classification majorly surface around ordering our knowledge in a manner that contributes to the economy of thought with an intention to recall the properties of the classified objects and learn new links in the properties being classified. Doing so permit us to form classes in a useful approach for practical and apply these to:

- Predict the behaviour of the soil mixture available.
- Identify their best utility and analyse them.
- Calculate an estimate of their productivity.
- Provides material for various geotechnical and geo informatics based research.

IV.PHOTOGRAPH PROCESSING AND CLASSIFICATION

Many soil characteristics, namely particle size (clod/aggregate), texture, colour, or a combination of attributes, can be taken into consideration when classifying soil. For classifying soil photographs, digital photograph processing and computer vision techniques is utilized. Analysing its colour allows for the effective acquisition of significant amounts of soil data since colour is a comprehensive indicator of the physical features and chemical compositions. Another characteristic that has been utilized in several methods to identify the kind of soil is soil texture, namely clay, silt, and sand. The estimation of pH value for soil characterization and categorization has also been studied. Considering this, the approach of classifying soils and making qualitative distinctions based on their colour and texture is one that is frequently employed. Scholars' pursuit of creating automated methods, intended to replace traditional, expensive manual approaches, for topographical division based on soil photographs into spatial entities for soil classification and delineation has increased. Recently, several algorithms based on traditional photograph processing and computer vision methods have been advocated by Hans Winterkorn et al [18

A. Reaching textural analysis: An important feature of any object, that enables one to visualize and characterize it, is its texture. Thus, a new classification method is constructed to employ data like hyperspectral soil textures that lay out rich intrinsic properties. A retrieval-based procedure, proposed by Winterkorn et al [18], involves 4 steps:

- Using a transformation method on the initial soil picture.
- Applying statistical measures on both the source photograph and the altered image, characteristics of texture, colour, and shape are retrieved.
- Following the calculation of the Euclidean method's distance formula, classification is fulfilled.
- Concluding with the ultimate step of calculating the total number of accurate checks retrieved from the database.

B. Acquisition: We acquired the images required for the testing and training datasets from the web. The standard pixel size that has been utilized here is 256 x 256, has been kept uniform throughout.

C. Detection: The composition of soil particles of various sizes, namely sand, clay, and silt, also described as soil texture, is used to characterize the physical attributes and processes. The proper classification and characterization of soil texture aids in management choices for engineering applications and agricultural environmental operations. When compared to data from laboratory measurements, this method accurately predicted the fine and coarse soil fractions from the photos. Colour is a property that affirms details about a place's age, mineral composition, presence of humidified organic materials, supported crops, and other characteristics. Redoximorphic Features (RMFs) are the colour patterns that develop in soil because of coloration gain or loss relative to the matrix colour brought on by either reduction or oxidation of manganese and/or iron together with their transport. Furthermore, the said method establishes how soil moisture affects quantifiable Soil Redoximorphic Features (SRFs) and in what manner processing of the photograph affects how SRFs are measured. Under regulated lighting, photographs of soil cores were taken. Utilizing PCA analysis, pictures are classified during the testing stage, and index values and training variables are contrasted. The final pH is determined, therefore. Untrained pictures are 91% accurate, but trained ones are 100% accurate. In our case, we witness the photograph detected from the file that has been added to the code. This photograph includes all the testing and training data of the five major types of soil being, clay, gravel, loam, sand, and silt. With a total of 6125 images in 5 classes consisting of both the testing data in conjunction with the training data, the code advances to processing the data and identify the class of the photograph put to test.

D. Data processing: Data processing takes place when collected data is translated into usable information.. The distinction between deep learning and machine learning is whether automated data augmentation from the available dataset is used. Machine learning is the automatic discovery of important data structures. It is a subdivision of artificial intelligence with a goal of employing intelligent programs that render possibility for machines accomplish tasks with expertise.. In the initial stage, we created data for multiple soil types, majorly being, clay, sand, silt, gravel, and loam, connected down to the testing and training datasets. Techniques for deep learning are frequently developed and put into practice using computational neural networks.The quantity of nodes in a network determines its resilience; the denser the network, the further layers there may be. Data, model, and algorithm are deep learning's three main building blocks. Deep neural networks allow the computer to learn entirely from the data without any manual intervention. Giving it required input is critical for obtaining the greatest results from it. Although most types of 3D photos may be used as input, stereo images produce superior results because they have the benefit of being able to extract three-dimensional information from a situation without being impacted by lighting modifications as shown in Fig.2.

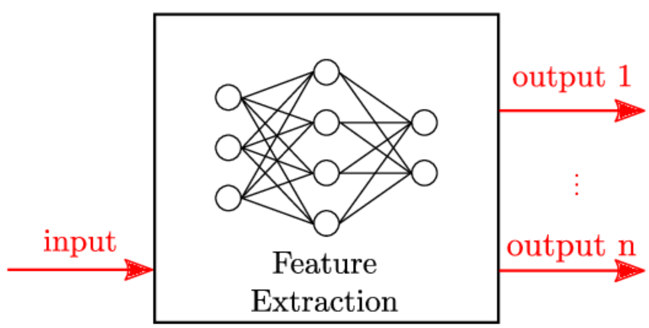

FIGURE 2. Output extraction model using machine learning.

Leveraging on the textural characteristics of the soil pictures, another feature introduced another classification method that uses multi-SVM and a linear kernel function. Images of this experiment were captured using a smartphone camera in the territory of West Guwahati. SVM can be applied to various class sizes except for loamy sand, silty clay, and loamy fine sand. This multi-class decoder worked effectively with the datasets. Hence, we decided to settle for the data to be processed for the five classes. When this was contrasted with standard experimental procedures, its technology verified to be far faster and more precise in classifying the type of soil.

E. CNN architecture: In this project, we have applied 32 layers wherein 2 convolutional layers are present. The model's foundational layer is a 2D convolutional layer (Conv2D) with a (3, 3) size kernel, and identical padding. The input form of the pictures in this layer is (256, 256, 3), which is the typical size of a jpg image, further described better in Fig.3. It also features a rectified linear unit (ReLU) activation function. A max-pooling layer (MaxPooling2D) with a pool size (2, 2) is drawn upon. Ultimately, the size of dense layers processed for output is 5.

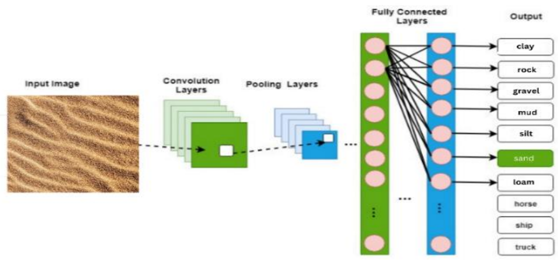

FIGURE 3. CNN architecture used for soil classification.

V. RESULT AND DISCUSSION

The software that has been utilized for the running of the code is jupyter notebook and google colab, in python language, entirely on a DELL inspiron 5482, 8GB RAM.

A. Confusion matrix: It is an error analysis technique that enables us to calculate the validity of the classification model. It permits an individual to assess and correct the errors made in their respective classification model. The matrix shows how many True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are generated using the testing dataset.

TABLE 1. A basic confusion matrix for binomial classes

TP	FP
FN	TN

B. Confusion matrices for the testing data: For our testing data of 151 images, with a total of 32 images in the clay (S1) dataset, 29 in gravel (S2), 30 in loam (S3), sand (S4) and silt (S5) respectively. For our testing *data of 151 images*,

- S1 – clay - 32
- S2 – gravel - 29
- S3 – loam - 30
- S4 – sand - 30
- S5 – silt – 30

Thus, enabling us to create the following confusion matrices –

TABLE 2. S1 confusion matrix

26	6
7	112

TABLE 3. S2 Confusion Matrix

21	8
9	81

TABLE 4. S3 Confusion matrix

24	6
5	51

TABLE 5. S4 Confusion matrix

24	6
5	25

TABLE 6. S5 Confusion matrix

25	5
5	111

C. Calculation: We applied assorted formulae with the aim of computing the accuracy, precision and other parameters such as false positive and negative rates and so on. To do so, the consequential table of formulae were applied.

TABLE 7. Formulae for parametric calculations

Accuracy	ACC = (TP+TN)/(P+N)
Sensitivity	TPR = TP/(TP+FN)
Specificity	SPC = TN/(FP+TN)
Precision	PPV = TP/(TP+FP)
False positive rate	FPR = FP/(FP+TN)
False negative rate	FNR = FN/(FN+TP)
F1 Score	F1 = 2TP/(2TP+FP+FN)
False discovery rate	FDR = FP/(FP+TP)

D. Results:

TABLE 8. Final results obtained after calculation

Soil Type	ACC	TPR	SPC	PPV	FPR	FNR	F1	FDR
S1	0.917	0.788	0.949	0.812	0.051	0.800	0.800	0/187
S2	0.857	0.700	0.910	0.724	0.089	0.300	0.712	0.276
S3	0.872	0.828	0.895	0.800	0.105	0.172	0.814	0.200
S4	0.817	0.828	0.807	0.800	0.193	0.172	0.814	0.200
S5	0.932	0.828	0.957	0.833	0.043	0.172	0.833	0.172

Thus, the results come down to be the following:

1. overall accuracy = 0.87826 = **87.826%**
2. overall precision = 0.79398 = **79.398%**

E. Graphs: We have generated some graphs to further analyze and provide information regarding the accuracy and loss of our model with respect to the testing dataset as well as the training dataset. Fig 4. Shows the representation of the accuracy of the model reading the dataset whereas, Fig 5. Depicts the loss of data that remains unrecognized.

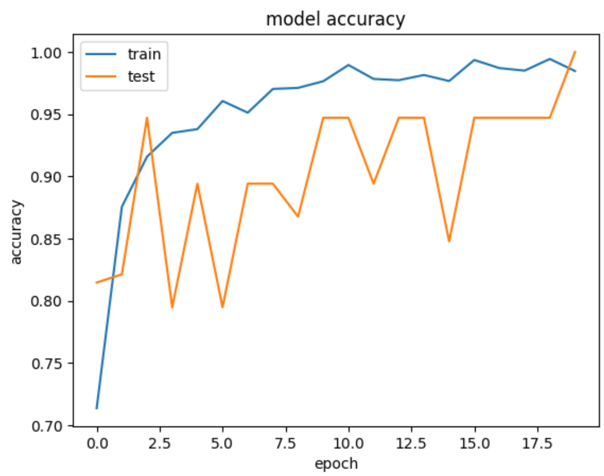

FIGURE 4. Graphical representation of model accuracy

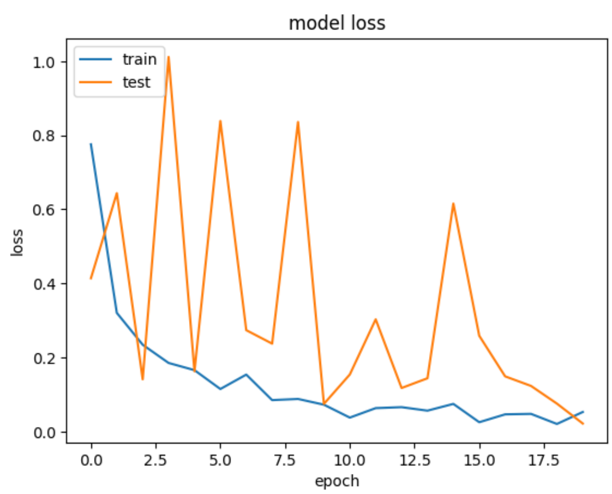

FIGURE 5. Graphical representation of model loss

VI. CONCLUSION

This research evokes a discussion on soil types and their attributes, which enable easy identification, besides a straightforward approach to a CNN model that classifies soil based on recognition. This program can be drawn upon by civil engineers besides secondary high schoolers for a better understanding of the soil types. It adds significance to civil engineering by providing scope besides precise recognition without having to tune down to the traditional methods previously employed. This paper invites scope for improvement besides further concerning trends in change of technology besides growth in the geo technological and agronomic fields. It alleviates issues by providing for simpler uses. Its addition to an application for future utilizations enforces advancement in society. With more intense studies keeping up with technical trends, we hope to improve the quality of the model developed along with the boost of precision in value recordings. This paper contributes to the existing works by adding a better accuracy rate by simplifying the endeavor of identifying soil types.

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