A comprehensive review on soil classification using deep learning and computer vision techniques

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A comprehensive review on soil classification using deep learning and computer vision techniques

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Abstract
Soil classification is one of the major affairs and emanating topics in a large number of countries. The population of the world is rising at a majorly rapid pace and along with the increase in population, the demand for food surges actively. Typical techniques employed by the farmers are not adequate enough to fulfill the increasing requirements and therefore they have to hinder the cultivating soil. For proper crop yield, farmers should be aware of the correct soil type for a particular crop, which affects the increased demand for food. There are various laboratory and field methods to classify soil, but these have limitations like time and labor-consuming. There is a requirement of computer-based soil classification techniques which will help farmers in the field and won't take a lot of time. This paper talks about different computer-based soil classification practices divided into two streams. First is image processing and computer vision-based soil classification approaches which include the conventional image processing algorithms and methods to classify soil using different features like texture, color, and particle size. Second is deep learning and machine learning-based soil classification approaches, such as CNN, which yields state-of-the-art results. Deep learning applications mostly diminish the dependency on spatial-form designs and preprocessing techniques by facilitating the end-to-end process. This paper also presents some databases created by the researchers according to the objective of the study. Databases are created under different environmental and illumination conditions, using different appliances such as digital cameras, digital camcorder, and a smartphone camera. Also, evaluation metrics are briefly discussed to layout some graded measures for differentiation. This review serves as a brief guide to new researchers in the field of soil classification, it provides fundamental understanding and general knowledge of the modern state-of-the-art researches, in addition to skillful researchers considering some dynamic trends for future work.

Keywords Soil classification · Deep learning · Convolutional neural network · Computer vision · Soil science

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1 Introduction

Soil classification is a productive research specialism, from the composition of the arrangement itself, to the definition of degrees, and finally to the application in the field. In the recent years, there has been a hike in interest for research in the field of soil texture and color classification using digital methods on images of soil. There are different lab and field conventional methods are used to perform soil classification. Usually engineers classify soils as per the engineering properties. Recent classification systems are depicted to enable a trouble-free transformation from field survey to primary predictions of soil engineering behaviors and properties. Soil section images produced via digitization methodology, using traditional cameras, microscopes or scanners under polarized light show a considerable assortment of geometrical traits. Soil classification can be commenced from the outlook of soils as a resource and soil as a material. The word soil is acquired from the Latin language word 'solum' which means floor. In eyes of a layman – soil is the dust or detritus on the earth surface. For a mining engineer the soil means the scattered pieces of rubbish or remains enveloping the rocks or minerals that he is extracting or mining. For a highway engineering the soil is the matter on which a track-bed is to be laid. For an agriculturist soil is an environmental medium for growing plant. The notion of soil as a natural body arisen from its potential to facilitate and support crops.

Soil characteristics play important role in evaluating different agriculture related tasks and therefore, have impact in agriculture engineering. Understanding the soil characteristics could lay out beneficial information to devise a better logical and well circumspect management scheme and use them in cultivating areas. Biota, geological history and climate are the important aspects which affect soil's chemical and physical properties at excessively (continental and regional scale), while dominant factors would be topography and human activities control the soil characteristics at smaller levels. The fundamental components of soil are the discrete fragments (e.g., plant fragments, clay minerals, quartz grains) which can be observed in disintegrated from using optical microscope. Structure of soil is directly related with the sharpness, shape, contrast frequency, size, voids and spatial arrangement of key particles. Moreover, many of such traits are dependent on the alignment of constituents and also the way in which they are cut as well as on the magnification used.

Conventionally, there are various methods to determine the soil texture and soil color. Numerous methods for laboratory and field use are pipette method, elutriation method, decantation method and Munsell color chart method. For soil classification USDA triangle method is also available. The downside of these methods is that they are labor and time consuming processes. Therefore soil classification has gained attention of researchers to use computer vision and image processing based methods in order to classify soil. In regards of the field study, the rural farmers don't have much information or knowledge about the texture of the soil. They are farming with very less prior and proper testing and are oblivious in regards with choosing soil according to the crops they want to grow. This affects the by and large (overall) growth of the crops. So, the farmers should be equipped with such a solution that is hassle free and provides knowledge about the soil they are using to grow crops accordingly.

Other than the conventional methods, several computer based methods and algorithms have been proposed in the past years. These methods only require images of the soil to work upon. Different algorithms are applied on the images according to the interest in the form of the results. Soil classification can be performed based on different properties of soil such as color, texture, particle size. Moreover, soil maps can be created using data like topography and vegetation as soil covariates to obtain an elaborated soil classification. Along with soil classification such methods can also be utilized to determine soil pH index and tillage quality without any human intervention. According to today's scenario, soil classification can be performed using two different stream depending on whether the features are handcrafted or generated through the output of deep neural network.

First is image processing and computer vision based soil classification. It is composed of four major steps: 1.Image acquisition 2. Segmentation 3. Feature extraction 4. Soil classification. First a soil image database is created using a camera set-up. Second, if there is need to segment the region of interest, segmentation is applied. Third, various textural and color features are extracted. And finally a pre-trained classifier such as random forest produces the identification outcomes utilizing extracted features. Figure 1 shows typical digital image processing cycle for soil classification. On the other hand, conventional applications using handicraft attributes, deep learning has come out as a common application to machine learning, which yields state-of-the-start results in many computer vision and image processing studies with availability of huge amount of data. Adaptive selection of features can be used for dimensionality reduction and improving accuracy. The features with high discrimination [25, 29], high accuracy [28] and low correlation [24] are good to be selected. The number of the selected features is less than that of the original features. The selected features maintain their original forms, so it is easy to observe the true values of the features. Several features, including color, texture and shape, can be used for soil classification, therefore dimensionality reduction methods can be incorporated to improve accuracy. Dimensionality reduction can be briefly categorized into two classes, namely subspace and feature selection. Subspace methods include PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis), RP (random projection), etc. Compared to PCA and LDA, RP can be free from training and therefore is much faster. Some extensions of RP were proposed, including two-dimensional RP (2DRP) [27], two-directional two-dimensional RP ((2D)^2RP) [26], sparse RP [23], which require far lower computational complexity and storage cost than traditional 1DRP.

Deep learning applications mostly diminishes the dependency on spatial-form designs and preprocessing techniques by facilitating end-to-end process to occur straight from input images. Among the various deep learning designs, convolutional neural network (CNN) has proven to be one of the accepted network model. In CNN model, input is convolved direct to a stock of filters in the hidden layers to generate feature maps. Every one of the feature map is identified as belonging to a particular level based on the output of softmax algorithm. Sometimes both the approaches, image processing and deep learning approaches, are employed together to get better results. For instance, color, texture and shape are analyzed

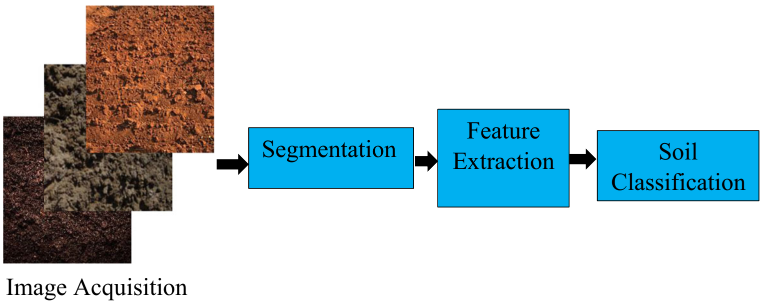

Fig. 1 Typical digital image processing cycle

using statistical measures and classified using support vector machine (Srunitha and Padmavathi [46]). Some of the methods introduced using deep learning in other fields could also be used in soil classification. Yang et al. [54] presented a color classification method of stool medical images which has great importance in clinical examination. In this work, classification task is performed by using CNN dubbed StoolNet. The accuracy for the presented work was 97.50% with low cost. Again in 2020, Leng et al. [30] introduced a light-weight practical framework for feces detection based on CNN for the use in real hospital environment. This research reported accuracy rate of 98.40% with low computational complexity and storage. This was performed on 6336 fecal images.

1.1 Contribution of this review

In spite of the recent work related to soil classification, there are none exhaustive literature surveys and reviews in the subject of soil classification using image processing, machine learning and deep learning methods. In various review papers the focus has been kept entirely on traditional image processing and computer vision researches without introducing machine learning or deep learning based approaches. Although, just a single survey of distinction across traditional and computer based application was presented. Thence, this paper is dedicated to a literature review, from conventional image processing to advanced machine and deep learning approaches. The main offerings of this review are as follows:

- The main center-point is on laying out a common comprehension of the state-of-the-art soil classification approaches, which can help new researchers in acquiring some knowledge about the crucial parts and trends in the machine and deep learning based soil classification field.
- Various database that have similar kind of soil images as well as different kinds of soil images, which the researchers have created themselves in different environmental conditions according to the need of their work.
- Key aspects is also reviewed of image processing based soil classification and deep learning based soil classification approaches are discussed. However, generally deep learning based soil classification methods lay out better performance than the conventional techniques, it also demands a huge amount of processing capacity, such as central processing unit and graphic processing unit.

1.2 Organization of this review

The rest of this paper is arranged as follows. In Section 2, fundamentals of soil science are discussed briefly. It explores some of the main terminology related to soil science, which makes it easier for readers to continue with the next sections. It also includes a brief description about the soil orders in tabular form in Table 2. In Section 3, soil classification approaches based on image processing and computer vision techniques are presented. It also gives a comparative review of these approaches arranged in chronological order in Table 3. In section 4, various soil classification approaches based on machine learning and deep learning and are presented. In section 5, a brief discussion about the soil image databases created by different researches according to the need of their study is presented. Section 6 gives a brief review of the evaluation metrics used for the soil classification algorithms. Finally, Section 7 offers some concluding remarks and challenges in the field of soil classification.

2 Fundamentals of soil science

Soil science is the study of soil dealing with soil as a unprocessed asset on the surface of the Earth involving mapping, genesis and classification (pedology), soil formation, fertility, chemical, physical and biological traits of soils and relation of these traits to the management and use of soils and crop production. Table 1 shows some designations of master horizons in the new and old systems.

2.1 Soil classification and its purpose

Classification means assembling objects into the section in some sequential and logical manner. It relies on the properties of these objects for the motive of studying and identifying. The various motives of soil classification are:

- To order our knowledge in a way that it contributes to economy of thought.
- To recall the properties of the classified objects.
- To learn new links and ideas in the properties being classified.
- To form classes in a useful way for practical and applied purposes to:

– Predict their behavior
– Identify their best uses
– Estimate their productivity
– Provide objects for research
– Extrapolate research findings to other areas

2.2 Soil order

There are twelve soil orders, they are based on morphology as produced by soil-comprising procedure and designated by the absence or presence of main diagnostic horizons. A layer which is approximately parallel to the soil surface and has traits that are lay out by soil-forming processes is known as soil horizon. Table 2 discusses the general features of soil orders briefly.

Table 1 Designations of master horizons in the new and old systems

Horizon designation		Short Description
New	*Old*	
O	A1	Organic horizon
A	A1	Mineral horizon
E	A2	Mineral horizon
C	C	Horizon or layers excluding hard bed rock
R	R	Hard bed rock

Table 2 Short description of Soil Orders

Soil Order	General Features
Alfisols	Alfisols develops in humid and sub-humid climate with a mean yearly precipitation of 500–1300 mm. They are frequently under forest vegetation.
Andisols	Andisols is soil with over 60% volcanic ejecta (pumice, ash, basalt, cider) with density below 900 kg\m^3.
Ardisols	Aridisols exists in dry climates.
Entisols	Entisols only have a shallow marginal A horizon and no other profile development.
Gelisols	Gelisols soils are found in very cold climates that holds permafost within 2 m surface.
Histosols	Histosols are organic soils (mucks and peat) made up of shifting depths of collected plant remains in marshes, swamps and bogs.
Inceptisols	Inceptisols have weak to moderate horizon development especially in humid regions. Horizon development is decelerated due to waterlogged soils and cold climate
Mollisols	Mollisols are often beneath grassland, but with some broadleaf forest covered soils.
Oxisols	Oxisols are developed only in sub-tropical and tropical climates.
Spondosols	Spondosols are normally the leached and sandy soils of cold coniferous forests.
Ultisols	Ultisols are immensely weathered soils in sub-tropical and tropical climates.
Vertisols	Vertisols are mostly found in tropical climate with definite dry and wet seasons. These have high content of clay which swells when wet and show cracks when dry.

3 Image processing and computer vision based soil classification approaches

Soil classification can be performed keeping focus on different features of soil, such as soil particle size (clod/aggregate), texture, color or combination of features. Digital image processing and computer vision approaches can be employed on soil images for classification. Color is an extensive measure of the physical characteristics and chemical compositions of soil, so a substantial measures of soil statistics can be productively acquired by analyzing the soil color. Soil texture in another property which has been used in various approaches to determine the soil type, mainly clay, silt and sand. Work has also been done on prediction of pH value for soil characterization and classification. On that account, the process of soil classification and qualitative distinction basing on color texture of the soil is very often used method. There is an expansion in the interest amongst the researchers for evolving automated processes for topography division based on soil images into soil spatial entities which aimed to replace conventional, expensive manual procedures for classifying and delineating soils. Various algorithms have been proposed in the recent past based on conventional image processing and computer vision techniques. Figure 2 shows a process with an input and an output, according to which the techniques can be decided. This section gives an elaborate review of such techniques used to classify soil proposed by various researchers and with different success rates.

3.1 Approaches with textural features

Texture is a characteristic which let us know the salient properties of a soil image which is generally known as the local statistic property of a parts with constant or varying models. In the past several years, there has been a lot of interest in the soil classification research based on textural features. Zhang et al. [58] proposed such a soil texture classification system which employs wavelet transform method to identify soil with different textures. Features are extracted using wavelet transform, which is a powerful image and signal analysis tool due

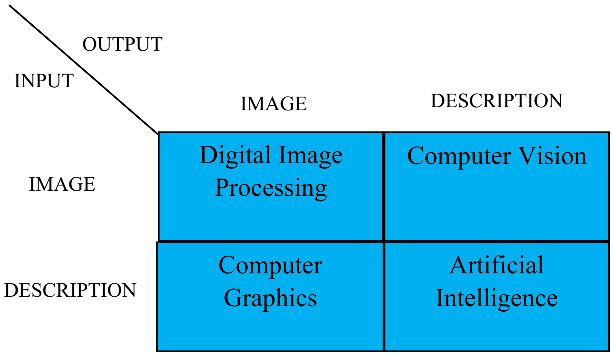

Fig. 2 Decision for Image processing and Computer vision techniques based on input and output

to its multi-resolution properties. A classifier called maximum likelihood (ML) is designed using a set of training instances. This ML parameter estimation method outputs optimum results. The Fisher's Linear Discrimination Analysis (FLDA) is employed to optimize and reducing dimension of vector at the time of training as well as classification. Clay, sand and silt are used as soil textures for training and classification. The classification rate for clay, sand and silt are 60%, 100% and 100% respectively. Zhang et al. [59] proposed an automated soil texture classification system using wavelet-based statistical models along hyperspectral soil signatures. In this study, a new system is developed using features like hyperspectral soil textures laying out rich intrinsic traits, where two models i.e. hidden Markov models and maximum- likelihood, are employed for classification. The HMM classifier in 3-class method gives accuracies of 100%, 97%, 89% for 89%, 97% and 100% for sand, silt and sand dominant textures respectively.

Chung et al. [36] investigated a method for soil texture classification based on RGB form images. Employing a miniaturized CCD camera, four surface images were taken for each segmented soil sample. Also pipette methods was used to determine texture fractions. USDA criteria was used to classify soil and it was observed that the in-situ image processing method and the laboratory method produced the same results for 48% of the soil samples. Shenbagavalli and Ramar [42] proposed a soil texture classification algorithm utilizing mask convolution. Feature extraction 3×3 Law's mask convolution were applied to examine soil images. To create the feature vector for further processes absolute mean, mean, skewness, kurtosis and standard deviation of the soil image were calculated.

Sofou et al. [45] proposed a computer vision based texture analysis on an image. For segmentation, the morphological partial differential equation based method depending on image contrast was used. For analyzing surface texture image variations as local modulation component was proposed. Breul and Gourves [10] presented in field method for soil characterization based on textural features using third order moment. In field proposed experiments uses textural investigation based on spectral methods applied to sub-surface soil images. This method aims to characterize high percentage of 80 m fine grained materials and speedily differentiate it from coarse material. Shenbagavalli and Ramar [43] proposed a soil image retrieval system. Outcome of the concluded that the proposed retrieval system performs efficiently. This retrieval based procedure involves 4 steps:

1. Application of transformation technique on original soil image.

2. Texture, color and shape features are extracted using statistical measurements transformed image as well as original image.
3. Perform the classification step by calculating the distance formula of Euclidean method.
4. Finally calculating the accuracy to determine the number of successful retrievals from the database.

Honawad et al. [21] proposed a soil classification method using Gabor Filter, color quantization and Low mask on the original soil images in order to extract textural features of images for retrieval. On a database of 100 soil images which belongs to 10 distinguished kinds of soil with different translation, scales and orientations this method showed effective retrieval performance. Another method developed relies on the soil color properties using colorimetry (Murti and Satyanarayan [34]), RGB color systems (Botelho et al. [9]) and Munsell (Chung et al. [14]). But these methods have shown very bad statistics capability for texture classification. Multivariate image analysis (MIA) is a very useful method incorporated by computer vision field amalgamating image processing for digital images and statistical multivariate analysis. Morais et al. [15] presented environmentally-friendly MIA-based analytical method which characterizes soil texture utilizing computer vision application in order to establish the quantitative assignment of soil's main constituents (sand, clay and silt) using DIP along with multivariate calibration. Figure 3 illustrates the analytical process to predict sand clay contents using image analysis. Sudarsan et al. [48] developed a computer vision algorithm based on CWT in order to categorize size of particles in the soil interpreting digital images captured using microscope. To categorize the extent of physical properties and processes of soil, percent distribution of soil particles of varied sizes (sand, clay and silt) which is called the soil texture is utilized. Proper soil texture categorization and characterization help management decisions for engineering applications and agri-environmental operations. This algorithm showed satisfactory prediction of the fine and coarse fractions of the soil from the images when compared to laboratory measured data.

3.2 Approaches with color features

Color is a characteristic that let us know traits like crops that are supported in that land, presence of humidified organic matter, mineral composition, age etc. The color patterns, called Redoximorphic features (RMFs), in a soil which are formed as a result of gain or loss in pigmentation in comparison with the matrix color caused by reduction/oxidation in manganese

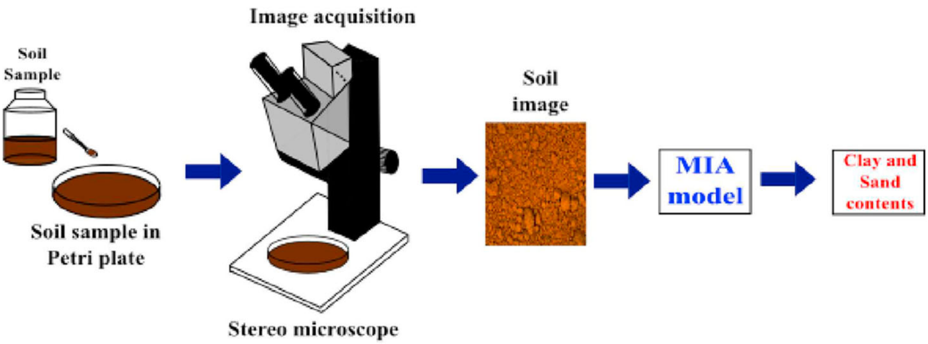

Fig. 3 MIA based method for clay and sand contents estimates (Morais et al. [15])

and/or iron combined with their translocation, accrual or removal. O'Donnell et al. [35] proposed a study which aimed to develop a Soil redoximorphic features (SRFs) quantification and identification system from soil cores by applying image processing and classification techniques on images created using a digital camera. Moreover, this system determines effects of soil moisture on quantified soil redoximorphic features (SRFs) and effects of image processing in interpreting SRFs metric. Images of soil cores were photographed under controlled light conditions. The overall accuracy of the system used for SRFs identification was 99.6%. Han et al. [19] proposed a new low-cost, smartphone-based and miniaturized soil color classification sensor after comparing and observing the roles of the machine vision and visible spectrum adopted in soil classification. Even though the system composition for soil classification based is easy and cheap, but it is also tough to control the ambient light and the machine parameters. The best identification rate was for yellow soil and burozem soil which was 100%.

Maniyath et al. [32] developed an efficient method to detect the soil color using DIP. Images are converted into HSV from RGB. The hue component are specified with an upper and a lower limit. Then this component is threshold and the image is converted back to RGB form. To determine the nearest example KNN system adopts a distance metric. Here Euclidean distance is used as distance metrics, however, various other distance metrics can be adopted. Pethkar and Phakade [37] utilized color moment, hsv, wavelet transform and Gabor filter feature extraction methods onto original images and extracted texture features of soil images for classification. Classification is done by SVM (Support Vector Machine). This paper also suggested that SVM can be replaced with ANN technique for classification. Results show that proposed method performs soil classification effectively. Overall accuracy of the system reported is 100%. Gurubasava and Mahantesh [18] proposed a digital image processing based methods and techniques to determine and analyze pH value from Agricultural soil. The term pH is used to classify the extent of basicity or acidity. Plant growth is affected by soil alkalinity or acidity. Proposed system extracts main features as the RGB index-values and compute the mean values by applying PCA analysis. In testing phase, classification of images takes place using PCA analysis and index values are compared with the trained values. As the result, the final pH is obtained. The accuracy of trained images is 100% and of untrained images is 91%.

3.3 Approaches with other features

Present day implementations of digital image processing (DIP) is concerned to assembly of features in soil's thin section with illumination sources like reflected light and plain transmitted, between circularly polarized light, crossed polarizers with gypsum plate (Protz and Van den Bygaart [51]; Terribile and FitzPatrick [50]; Protz et al. [38]). Aydemir et al. [2] proposed a study which aims to investigate implementation of method which uses a single light source to quantify and classify distinguished features (mineral and non-mineral) from thin soil sections at the macroscopicscale. Unsupervised classification verifies to be a powerful tool with the Nearest Neighbor classifier as the well performing method. It observed accuracy greater than 95%.

The physical state of soil in terms of its acceptability in planting and growing a crop is known as soil tilth. Determination of the tilth includes features such as stability and formation of accumulated soil particles, soil biota, degree of aeration, moisture content, rate of water drainage and infiltration. Bogrekci and Godwin [8] presented research work to determine the size of clod/ aggregate dispensation by employing computer vision as a mensuration technique. Three different soil tilths were used to acquire digital images, soil tilths namely: fine and intermediate sandy loam soils, coarse soil. Image-enhancement and geo-correction models were utilized to improvise the quality and geometric distortions present in the images. Images were passed by a 'virtual sieve' to estimate size of clod dispensation. Dornik et al. [16] presented an object-based methodology utilizing digital maps of vegetation and topography digital maps as soil covariates (in Random forest) in order to give an elaborated classification and delineation of soil class. 5 remote sensing indices and 18 digital elevation derivatives related to soil and vegetation cover were considered. For the use in segmentation procedure, RF model was employed to recognize the major soil type predictors. Shukla et al. [44] presented an effective implementation of Random Forest (RF) method and evaluation of the performance and behavior of soil classification model built for Indian districts. To tune the RF model soil-forming factors, called 'scorpan,' are chosen as covariates of environmental in order to classify 11 different categories of soil. To facilitate 'scorpan' environmental covariates 35 digital layers are composed by utilizing distinct satellite data [ALOS, Landsat-8, RISAT-1 etc] along with climate related data (such as temperature and precipitation) in the study area. Mapping accuracy, noise and sensitivity to the dataset size are calculated to evaluate the model behavior. For evaluating the performance of the model, Jaccard's coefficient and F-measure, marginal rates, agreement coefficients and classification success index are picked for quality analysis measures. High stability is shown by the RF model against dataset reduction in comparison to other methods. The study area comprises fertile land lying along the river Yamuna in India. The overall accuracy rate was reported to be 95.98%. The results provided by this work give new thoughts into the soil class mapping using Random forest model. Zhang and Hartemink [57] proposed a method to map the profile wall of soil order called Alfisol by employing digital soil mapping. To estimate a degree of properties throughout the soil profile, the digital images and geotechnical data were fed as input data to the models. For color and profile maps fuzzy c-means clustering is applied and a confusion index was calculated. Color coordinates corresponds to silt, sand and weathering indices and SOC (soil organic carbon). Random forest using CIE $L^*a^*b^*$ and hue, chroma, saturation, HSV models exhibits better predictions of SOC contents than using RGB model. Figure 4 shows comparison of performance of some of these approaches.

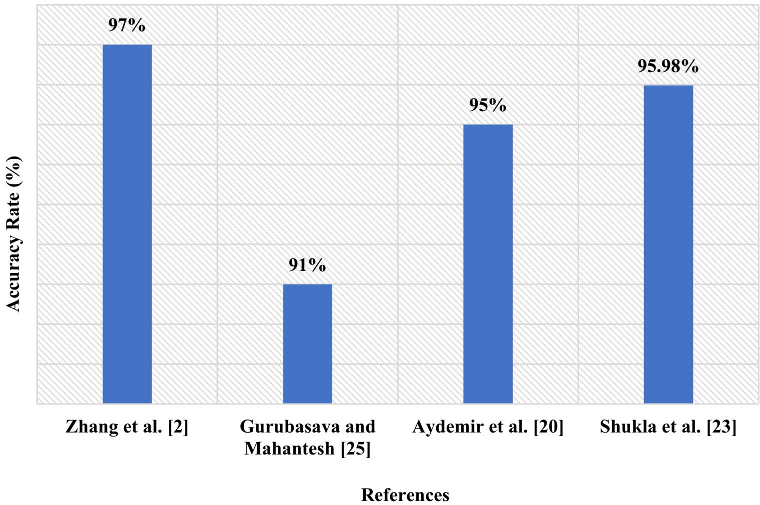

Fig. 4 Performance of some of the image processing and computer vision based approaches in Soil Classification

Table 3 summarizes the approaches is a tabular comparative manner. Columns 'References' denotes the research work and year in which it was published. Column 'Texture/Color' indicates the features which are focused upon in the study. Column 'Research configuration' gives a short description of the techniques used by the authors. Column 'Classifier' indicates the name of the classifier used the work by the authors. Column 'Accuracy' indicates the noted performance of the system. Column 'Database acquisition device' indicates the appliance which is used by the author to click the soil images to create the database. This discussion shows color based, texture based, particle based and tilth based soil classification employing the conventional image processing and computer vision techniques. It can be observed that using random forest model in the classification step gives better results. Also principal component analysis (PCA) used for dimensionality reduction reduces the complexity in the system. The databases are acquired using different appliances such as digital cameras, mobile phones and satellite. These types of approaches have proven to give satisfactory results, but the strength of the data is not sufficient as they have not more than 200 images. But the system should be made up for the number of images in hundreds, for this machine learning and deep learning approaches are available.

4 Deep learning and machine learning based soil classification approaches

The skill, known as classification, learnt by human via distinguished sources in many times of lives and then repeatedly used it to in executing the work. In artificial intelligence sphere, same function is performed by deep learning algorithms by learning through unstructured data like texts, sounds, images, videos etc. Automatic feature extraction or direct learning from the given data is the difference between deep learning and machine learning. Machine learning labels the automated detection of meaningful patterns in data. It is a division of artificial intelligence with aims to enable machines to perform the jobs skillfully using intelligent software. Figure 5 shows the learning process of machine learning models. Artificial neural networks are often used in designing and implementing deep learning algorithms. The strength of networks depends on the count of layers in it, more the layers deeper is the network and the number layer has no limit. The key components of deep learning are data, model and algorithm. Deep learning models can have hundreds of hidden layers. Every one of the layers in the network performs non-liner functions in parallel. Neurons makes possible connections between the layers, a layer performs on the output of the prior layer and transmits the result to the next layer for processing. Increasing the number of layers leads to complexity in the network. In deep neural networks there is no human influence on the machine, it learns directly from the data. Feeding it with proper and sufficient input is a necessary and crucial part to gain best of the network. However, many kind of 3D images can be fed as input, but stereo images yield better results as there is advantage of extracting 3D information from a scene being unaffected by changes in the conditions of light. Figure 6 shows the learning process of deep learning through different layers of neurons. Zhang et al. [60] proposed a mask-refined R-CNN for refining object details in instance segmentation. This is to learn the effects of semantic segmentation of high level and low level features on instance segmentation. The experimental results are collected on COCO (common objects in context) and cityscapes dataset. This method is said to be easily implemented and well performed. Chu

Table 3 Comparative summary of Soil Classification systems based on image processing and computer vision arranged in chronological order

References	Texture/ Color	Research Configuration	Classifier	Accuracy	Database acquisition device
Zhang et al. [58]	Texture	• Classification using Daubechies D4 wavelet • Feature reduction and optimization during classification by FLDA • Highest performance observed in classification of silt and sand	Maximum likelihood (ML) estimation	100%	_
O'Donnell et al. [35]	Color	• Quantification and identification of Soil redoximorphic features (SRFs) • Overall accuracy rate is given based on Munsell soil color chart employed for identification of SRF	Euclidean distances	99.6%	Nikon D80 digital camera
Han et al., [19]	Color	• Visible spectrum reflection traits of various kinds of soil • Visible spectra processed the principal component analysis (PCA)	Visible spectroscopy and Machine vision	100%	D7000 SLR kit, xiaomi2s mobile phone
Honawad et al. [21]	Texture, Color	• Content-based image re-trieval (CBIR) system to browse and search database • Soil classified as: sands, silts, loams and clays using color based features extraction color quantification • For textural feature extraction law mask and Gabor filter are applied. At the classification, crop prediction is also included	Statistical measurements	_	DXC-3000A Camera, Sony Corporation
Shukla et al. [44]	–	• Evaluation of behavior and performance using Random Forest • Reference data is acquired from pre-existing soil re-source maps(SRM) • Mean decrease gini (MDG) and Mean decrease accura-cy (MDA) are calculated	Random forest, Classification and regression tree (CART), CART ensemble bagger (CEB)	95.98%	Different satellite like ALOS, LANDSAT-8, RISAT-1, SENTINEL 1A
Gurubasava and Mahante-sh, [18]	Color	• With the help of color image processing, soil image pH index is calculated. Alkaline or acidic nature of soil is predicted	Principle component analysis (PCA)	91%	_
Sudarsan et al. [48]	Texture	• Characterization soil particle sizes • Soil variations divided into two class: fine fragments and coarse fragments	_	87% (Coarse) 88% (fine)	AD-7013MT USB digital microscope

Table 3 (continued)

References	Texture/ Color	Research Configuration	Classifier	Accuracy	Database acquisition device
Dornik et al. [16]	_	• Computed Global wavelet power spectrum (GWPS) • GEOBIA based on image segmentation for soil delineation and classification • 18 geomorphometric variables derived from the DEM using Saga GIS software and five indices related to vegetation cover	Random forest	58%	Landsat 8 satellite
Maniyath et al. [32]	Color	• Determination of soil color using DIP • RGB values of all the cropped color images from Munsell chart are used to train he classifier • Median filter is used in order to deal with mottled, grainy, textured or snowy appearance	K-Nearest Neighbor (KNN)	_	13MP mobile camera
Morais et al. [15]	Texture	• MIA associated digital images and analytical parameters using methods like PCA • Combined DIP and multivariate calibration to determine quantitative distribution of main constituents of soil: silt, sand and clay	MIA textural classification	100%	Digital camera integrated into a Leica EZ4 D stereo microscope

et al. [13] presented an object detection algorithm for occluded and small objects based on multi-layer convolution feature fusion (MCFF) and online hard example mining (OHEM). This work is carried out on KITTI dataset which has total 7481 images.

4.1 Approaches with textural features

Tillage operation is meant to improve the tilth of the soil. The physical state of soil in terms of its acceptability in planting and growing a crop is known as soil tilth. Determination of the tilth includes features such as stability and formation of accumulated soil particles, soil biota, degree of aeration, moisture content, rate of water drainage and infiltration. Perfect size of aggregates causes a better air to moisture fraction and so produces better outcome in terms of yield. Therefore for best desirable tillage conditions is to change the size of aggregates according to the requirement of the seed. Ajdadi et al. [1] developed a method for examining tillage quality using a real-time measurement employing artificial neural network (ANN). Textural features were extracted from tilled soil images using methods like gray-level run length matrix. Feature selection was employed using data mining method by CfsSubsetEval. Neural Networks with 19–19-

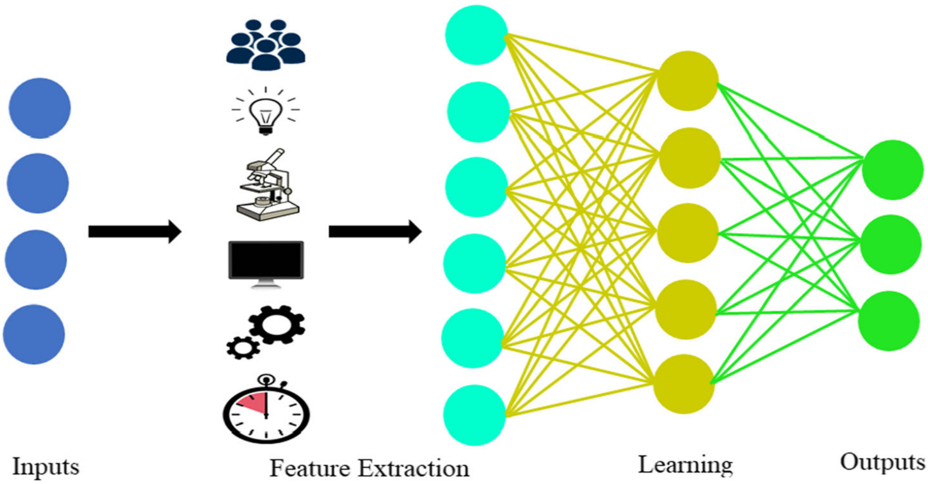

Fig. 5 A typical Machine Learning Model

1, 14–22-1, and 17–20-1 neurons resulted in the best classification. Images taken from height of 60 cm gave the best overall accuracy of the ANN classifier being 72.04%.

Barman and Choudhury [5] presented another soil classification system, employing multi-SVM and linear kernel function, based on the textural features of the soil images. The images for this experiment were acquired using a camera of smartphone and the area considered was West Guwahati region. SVM can be used with different number of classes. Here, multi-class classifier performed well on the dataset except the classes: loamy sand, silty clay and loamy fine sand. This system takes lesser time to classify the soil type as well as it is very accurate compared to the conventional laboratory methods. The classification rate of SVM for this system is reported to be 95.21%.

Wu et al. [53] presented a study in which 3 machine learning techniques were investigated for identifying the topography effects on the contrasting soil textures atop a watershed in

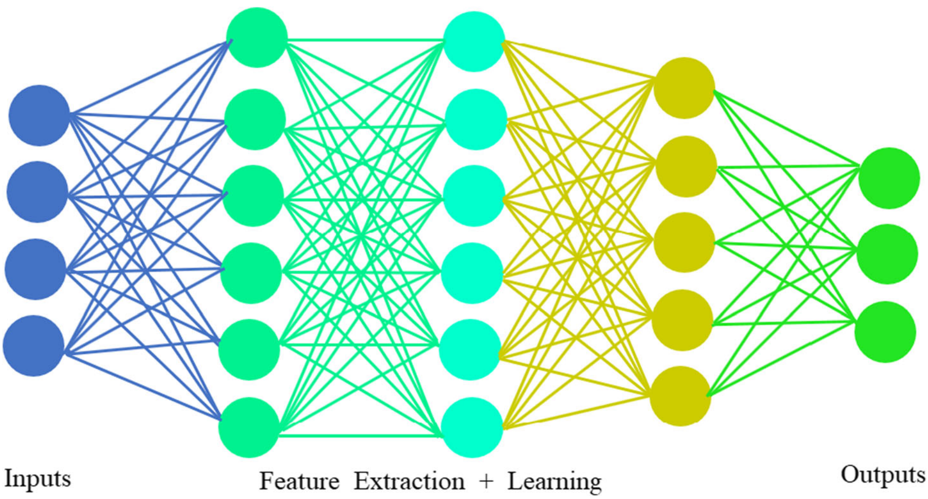

Fig. 6 A typical Deep Learning Model

southwest, China. While comparing the results it was observed that polynomial kernel function used by support vector machines (SVM) performed better than tree model and artificial neural network (ANN) for classification phase. The AUC, kappa value and overall accuracy of poly-SVM were 94.4%, 79% and 94.3% respectively.

Chandan and Thakur [12] presented a review on methods used for soil classification using machine learning techniques. In India, major 9 types of soils could be found which includes Forest soil, Alluvial soil, Black / regur soil, Red soil, Saline soil, Arid / desert soil, Peaty / marshy soil, Sub-mountain soil, Laterite soil, Snowfields. The developed techniques include k-Nearest Networks (k-NN), Decision Trees (DT), Support Vector Machines (SVM) and Artificial Neural Networks (ANN). Machine learning is used to classify soils based on various detectable features such as soil moisture content, soil nutrients, soil structure, soil quality, soil pH and soil texture.

4.2 Approaches with color features

The improvement and maintenance of effective soil parameters is basically the main focus for soil management in agriculture in order to enhance crop productivity. The prime factor for a highly fruitful new agriculture system is the crop health. Proper health management should be followed to increase the crop production. Timely detecting and controlling the issues related the crop yield makes the farmers to take the decision for appropriate crop management and soil resource management. In the recent time, Machine Learning (ML) techniques are being used in prediction and classifying such problems effectively, these ML methods also reduces the challenges faced in the computer based agriculture systems. Suchithra and Pai [47] proposed a system classifying soil pH values and soil fertility indices for the soil residing in north central laterite region as well as predicts the values based on soil parameters. Extreme Learning Machine (ELM) was employed for classification and prediction process to be faster, it is one of the second generation neural network methods. In this learning algorithm, feed forward neural networks observed to give the best generalized performance. Moreover, this learning algorithm has proved to be very efficient for Single hidden layer feedforward neural networks (SLFNs) without being complicated. It was observed that for K fertility index the accuracy rate is 78% and that for the classification of pH is 89%. When neural networks are used, one of the parameter used is the activation function. Here Gaussian radial basis displayed the best potential for fertility index and soil nutrient classification, in terms of performance as well as kappa and accuracy value. Other activation functions employed in this system were sine-squared, hard limit, triangular basis, and hyperbolic tangent functions. Aziz et al. [3] suggested a method to determine soil's pH value by employing Artificial Neural Network (ANN). Objective of this work is to find out the pH value of soil image samples based on soil color by employing neural network. For this a mean database is created. The RGB values of the test sample and samples stored in the database are compared to find the minimum error to evaluate the pH values. The neural network in this proposed work has three neurons in the input layer, ten neurons in one hidden layer and one node in the output layer. Three input neurons of the input layer are fed with the three colors of soil (RGB). Single output node give the pH value of the soil sample. Barman et al. [6] presented a system to determine the pH value of the soil such that there is no human intervention. To reduce the unwanted distortions from the soil images some image enhance techniques including image resizing, image filtering, and contrast improvement are used. The mean values of HSV components are calculated: Mean H, Mean S, and Mean V. Quadratic regression gives a better results for soil pH values recoded for Guwahati area of Assam.

Barman et al. [7] presented a digital process which predicts the soil pH in a simple and accurate way. In this process, soil image is captured with the help Smartphone and then images are segmented with the help of K Means algorithm and using Hue, Saturation and Value (HSV) features were determined using color image processing. The actual soil pH content is estimated through the laboratory pH meter method and the indexes are estimated from the HSV values. After comparing them with the regression method, find a better values for the soil sample images. Figure 7 shows few examples of the captured images as the dataset.

4.3 Approaches with other features

Selecting the crop(s) is one of the main issue in planning of agriculture. The major tasks in crop selection should be minimizing losses in unfavorable conditions as well as maximizing crop yield rate in potential favorable conditions. Machine Vision Systems (MVS) provides an alternative to manual inspection of soil samples based on the characteristic properties and the amount of nutrient material pf the soil. Rao et al. [40] proposed a method combining both the techniques, where classification of crop for appropriate soil is a part of classification of soil. The image contains errors like noise or artifacts like scratches, lapping tracks, comet tails etc. which needs to be eliminated before the further processes. So for image enhancement smoothing filters are used. K-means Clustering algorithm is employed for segmentation of the image. It is used as a partition clustering aiming to partition a given data set into separate subsets in order to optimize the specific clustering criteria. A number of features like the texture, color, intensity, saturation, hue, etc. are extracted for detection of soil type. Gabor Filter is implemented for feature extraction. An SVM model is employed for classification. This work has real-time relevance involving both pattern recognition techniques as well as image processing. Srunitha and Padmavathi [46] found out SVM classifier's performance on soil data employing color quantization technique, Gabor filter and low pass filter. Statistical parameters such as Standard deviation, HSV histogram and mean amplitude. The segments were classified using machine learning (ML) method support vector machines (SVM). For

Fig. 7 Few Samples of collected soil image databases (Burman and Choudhury [5])

image transformation color quantification, low pass filter and Gabor filter are used. This study achieve accuracy rate of 95% for classifying.

Some machine learning methods like decision tree, support vector machines and artificial neural networks have been suggested as possible techniques for soil mapping (Heung et al. [20]; Taghizadeh-Mehrjardi et al. [49]; Brungard et al. [11]; Zádorová et al. [56]; Wei and Shang [52]; Leiß et al. [31]; Kovačević et al. [22]; Ehret [17]; Zhao et al. [61]). Many of these focused on soil classification and results of these explorations established that the performance of models are variable under different circumstances (Heung et al. [20]; Brungard et al. [11]; Taghizadeh-Mehrjardi et al. [49]; Ehret [17]; Kovačević et al. [22]).

Mengistu and Alemayehu [33] presented a soil classification and characterization using hybrid approach of sensor network approach and computer vision. In this work along with image processing, gravity analog soil moisture sensor with arduino-uno is also employed for characterization and classification of soils. Classification and characterization is carried out using BPNN (Back-propagation neural network) with accuracy rate of 89.7%. Sharma and Kumar [41] proposed a system to analyze and classify the soil of Rajasthan, India in order suggest the farmers about the soil type, soil nutrient, suitable crops etc. For classification regression support vector machine was used. Rahman et al. [39] presented a model whose prime motive was to generate suitable model to classify many kinds of soil series as well as suggested suitable crops for 6 Upazilla of Bangladesh. Numerous chemical features were used by the machine learning methods to recognize the soil series and viable crops for that soil series were suggested using geographical attributes. Three different methods used were Bagged Tree, Gaussian Kernel based SVM and weighted K-NN. SVM showed best accuracy i.e. 94.95% out of the other methods used in this work. Yu et al. [55] proposed 3D-CNN system for soil classification exploring a liquid crystal tunable filters (LCTF). The hyperspectral images of soil were restored in better resolution using compressive sensing (CS) method used for spatial and spectral domains. In the spectral domain principal component analysis (PCA) for dimensionality reduction is employed. Overall accuracy reported by this method was 99.59%.

Azizi et al. [4] proposed a study of classifying soil aggregates of random size in the particular classes by using deep learning. The process of aggregate classification is shown in Fig. 8. The proposed deep model observes and extracts the required features from simple to complex features automatically, unlike the conventional computer vision and image processing algorithms where features are extracted manually. Here, convolutional neural network (CNN) was employed from various deep learning algorithms. Other than this, ResNet50, Inception-v4 and VggNet16 architects were also used to train the model. The highest accuracy achieved with ResNet50 i.e. 98.72% whereas the classification accuracy of the networks reported above 95%. Figure 9 shows comparison of performance of some of these approaches.

Table 4 summarizes the deep learning and machine learning based approaches is a tabular comparative manner. Columns 'References' denotes the research work and year in which it was published. Column 'Texture/Color' indicates the features which are focused upon in the study. Column 'Research configuration' gives a short description of the techniques used by the authors. Column 'Classifier' indicates the name of the classifier used the work by the authors. Column 'Accuracy' indicates the noted performance of the system. Column 'Database acquisition device' indicates the appliance which is used by the author to click the soil images to create the database. Somehow it can be observed from this discussion that deep learning and machine learning based approaches give approximately similar results as that of the approaches mentioned in the previous section. But as the time going by deep learning and machine learning are gaining importance because a large amount of data can be fed to the

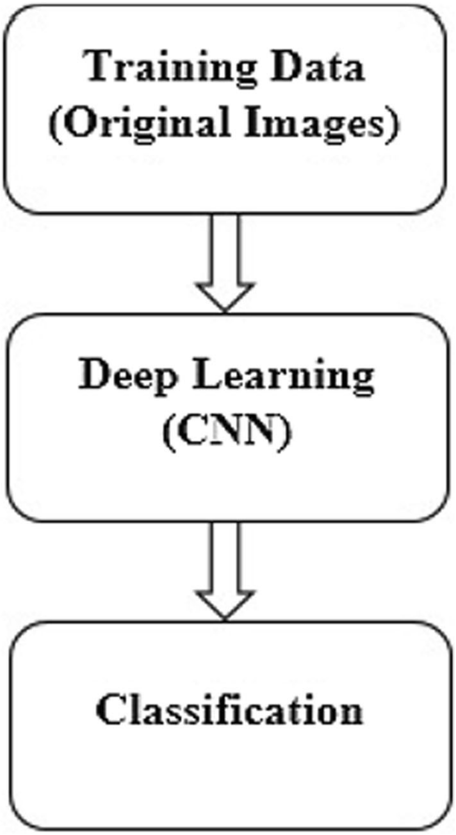

Fig. 8 Classification using deep learning method called Convolutional neural network (CNN). (Azizi et al. [4])

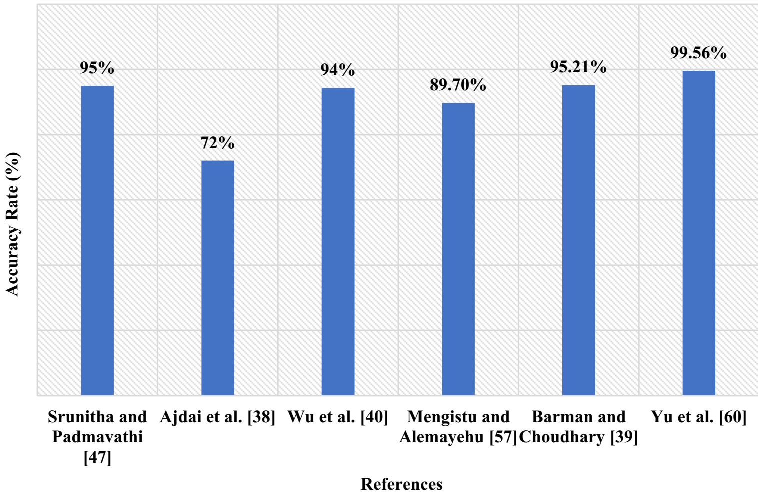

Fig. 9 Performance of some of the Deep Learning based approaches in Soil Classification

Table 4 Comparative summary of Soil Classification systems based on deep learning and machine learning arranged in chronological order

References	Texture /Color	Research Configuration	Classifier	Accuracy	Database acquisition device
Srunitha and Padmavathi [46]	Color, Texture	• For image transformation color quantification, and for feature extraction 2D gabor filter used • Dataset consists of a collection of 175 soil sample measures. • Color, texture and shape are analyzed using statistical measures	7-class Support vector machine (SVM)	95%	_
Ajdadi et al. [1]	Texture	• Machine learning based real time tillage quality measurement • Textural information extracted using local binary patterns etc. • 9 different soil aggregate size up to about 100 mm were considered • Data mining is performed using CfsSubsetEval	Artificial neural network (ANN)	90.32%	Digital camcorder Canon PC1586
Aziz et al., [3]	Color	• Determination of soil pH by soil color using neural network • 15% (8 samples) of data used for testing 70% (34 samples) of data is used for training and 15% (8 samples)of data is used for validation	ANN	_	_
Rao et al., [40]	Color, Texture	• Classification and grading of soil samples along with crop detection • Segmentation is performed using K-means clustering algorithm • Texture, color, intensity, saturation, hue entropy, standard deviance, mean extracted using Gabor filter	Decision tree, ANN, SVM	_	_
Wu et al. [53]	Texture	• Various of terrain indicators derived from digital elevation models (DEMs) along with soil properties as features • Best accuracy observed for SVM	SVM, ANN, Classification tree	94.3%	_
Mengistu and Alemayehu [33]	_	• autoCorrelogram, color_moments, hsvHist, wavelet_moments, meanAmplitude, msEnergy, used as features • Best accuracy rate is shown at 26 hidden neurons	Back propagation neural network (BPNN)	89.7%	Canon EOS Digital and IP camera
Barman et al. [6]	Color	• Preprocessing performed using image resizing, image filtering, and contrast improvement. • HSV values for each soil image: Mean H, Mean S, Mean V	Linear regression	84.9%	Xiaomi Redmi 3 s Prime
Yu et al. [55]	_	• Liquid crystal tunable filters (LCTF)-based system and proposed 3D CNN classification • To achieve dimensionality reduction PCA is applied • Reduction in the system size and acquisition cost achieved using compressive spectral imaging system	3D convolutional neural network (CNN)	99.59%.	DMD (DLP9500) consists of 1920_1080 Micro-mirror arrays
Barman and Choudhury, [5]	Texture	• Gabor filter model used for texture segmentation of the image and HSV, auto correlogram, color moment, DWT used as feature	Multi-class SVM	91.37%	Xiaomi Redmi 3 s Prime

Table 4 (continued)

References	Texture /Color	Research Configuration	Classifier	Accuracy	Database acquisition device
		• Loam and Clay Loam soil have the best accuracy rate: 96.84% and 96.2%			
Barman et al. [7]	Color	• K Mean clustering for image segmentation • RGB and HSV features extracted from each sample • The best fit coefficient value for this correlation is 0.823	Quadratic regression	_	Xiaomi Redmi 3 s Prime
Azizi et al. [4]	Texture	• Deep learning employed for classifying aggregates of any size in particular classes	CNN, VggNet16, ResNet50	98.72%	W3-Fujifilm stereo camera
Suchithra and Pai, [47]	_	• Area wise classification based on soil fertility index on the village level • Different ELM classifiers with the activation functions which include the hyperbolic tangent function (elm_- tanh), triangular basis transfer function (elm_tribas) etc.	Extreme Learning Machine (ELM)	89%	_

system for better results. One of the advantages of these techniques over the computer vision one's is that they perform well even on the images taken from android mobile phone. This makes the system very convenient. Also in deep learning there is no need to extract the features separately because the network generates the feature map itself.

5 Brief introduction to soil classification databases

In the field of soil classification, numerous databases have been employed for extensive and comparative investigation. Researchers, depending on the objective of their study, created soil image databases under different environmental and illumination issues. The databases have been acquired using different devices such as DSLRs and mobile phone camera. It is observed that there is difference in the set-up of the image acquisition system as well as distance of taking the photographs. Till this time, soil classification research using images has been covered for different lands in distinguished countries. This section covens a brief discussion of few research work in which the databases were created in different condition, it also covers a comparative review of these databases in tabular form.

- Han et al. [19] created the soil image database employing D7000 SLR kit made by Nikon Corporation for the experiment. The effective pixels of CMOS sensor and focal length ranges between 18 and 105 mm. distance between the soil surface and camera was 0.5 m. For the lighting device LED formed circular light was used and brightness can be approximately regulated in 10 levels. Ten images of each soil specimen were captured under ten different LED illumination. Then RGB signals of the 10 pictures were averaged. The experimental setup (Fig. 10) was placed in a dark room.
- Honawad et al. [21] captured images using camera (DXC-3000A, Sony Corporation, Japan) connected to a PC. Camera was setup over the light vestibule on a duplicate stick, which gave simple vertical development to finely tune the position of camera concerning soil parts. Images were captured using the software Matrox Intellicam for Windows. Illumination source was a fluorescent light tube, which provided even illumination over the field of view.

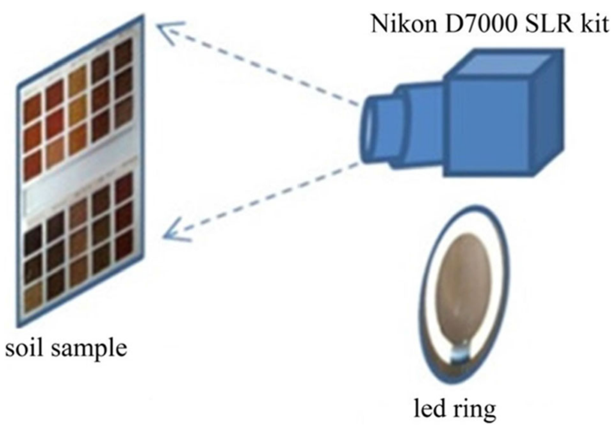

Fig. 10 The illustration of machine vision image acquisition (Han et al. [19])

- Shukla et al. [44] used different data sources and geo-referenced them assessing the Landsat-8 image. 35 digital layers were used to represent the environmental covariates in the study area. The covariates are basically obtained from different satellite data: MODIS NDVI product, Landsat-8, ALOS-DEM, Sentinel-1A, RISAT-1 and climatic data: temperature, precipitation.
- Sudarsan et al. [48] developed an image acquisition system employing a low-cost compact microscope with maximum magnification of 200× and 5 MP camera. Samples are collected from two agricultural fields (Field26 and Field86) with highly variable soils. Each sample of air dried ground soil served 3 images were captured in laboratory conditions. Total 123 soil samples were collected, 56 from Field26 and 67 from Field86. Triplicate in-situ images were also collected from 67 locations from Field86 after scrapping off surface residues.
- Barman et al. [6] captured the images (40) using a Redmi 3 s Prime with a resolution of 4160 × 2340 under visible light. Images have been captured with a distance of 10 in. from soil to the camera in order to avoid the uncontrolled illumination source.
- Maniyath et al. [32] created the database from Munsell soil chart images employing a 13megapixel camera of smartphone. Munsell chart has all color variants of a tone with different values of chroma and hue and chroma. Every color variant from these images are cropped in the size setup as 256 × 256 and named respectively.
- In Morais et al., [15] generated images from sieved and dried soil samples (2.0 g) on a petri-dish. A digital camera integrated with a Leica EZ4 D stereo microscope was employed to acquire images. RGB images with 2048 × 1536 pixels were recorded in set of three for each sample makes 189 total digital images.
- Burman et al. [7] captured soil images using a Xiaomi Redmi 3S smartphone with 13 megapixels. All the camera settings are maintained to default during capturing the images such as F-stop = f/2, exposure time = 1/60 S, ISO speed = ISO 125, focal length = 4 mm. Figure 11 shows the procedure of the image acquisition. Five samples are photographed from each of the field and a total of 50 soil samples are collected.

Table 5 displays a summary of various databases created by the researchers according to the need of the study. Column 'Data configuration' gives a short description of the databases created by the authors. Column 'Site location' indicates the city and/or country from where the soil samples are acquired to click the soil images. Column 'Device used' indicates the appliance which is used by the author to click the soil images to create the database.

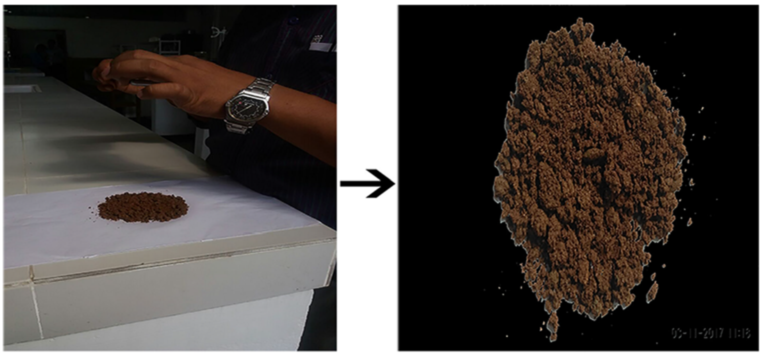

Fig. 11 Soil image acquisition setup using a smartphone (Burman et al. [7]))

Table 5 Summary of different Soil image databases created by distinguished researchers according to the need in the research work

References	Data configuration	Site Location	Device used
Han et al. [19]	• 50 soil samples per soil type • Photographed under different LED illumination intensities • Color calibration card is used	Beijing, China	D7000 SLR kit, xiaomi2s mobile phone
Gurubasava and Mahantesh [18]	• Data include 30 samples of soil with different color • Two different datasets are used on for training other for testing	–	Digital camera (name not mentioned)
Sudarsan et al. [48]	• 123 soil samples collected from two agricultural fields • Images gathered from 67 locations from Field86 by scrapping off surface residues • Three datasets are used: 1. 168 images 2. 201 images 3. 201 images	Quebec, Canada	AD-7013MT USB digital microscope
Dornik et al. [16]	• For datasets, a Landsat 8 satellite images containing 171 soil profiles and SPOT digital elevation model	Romania	Landsat 8 satellite
Morais et al. [15]	• Each sample serves triple images in RGB form with 2048 × 1536 pixels which makes 189 digital images from 63 topsoil sample • The count of color variables: 644 for RGB, 663 for HSV and 197 for Grayscale, represent the image matrix	Nova Canaa do Norte, Brazil	Digital camera combined with a Leica EZ4 D stereo microscope
Ajdadi et al. [1]	• From 3-levels of camera height from ground surface 60, 80, and 100 cm, photographs were clicked • For each class of aggregate size, about 150 images were taken	Rasht city, Iran	Digital camcorder Canon PC1586 with Canon Zoom Lens 4X and 12.1 Mega pixels
Barman et al. [6]	• Soil is collected from deepness of 6 in. from the surface of Earth • 40 soil image samples are collected	Guwahati, India	Xiaomi Redmi 3 s Prime
Barman et al. [7]	• 10 samples each from 12 paddy fields collected from a distance of 200 m • From the top level soil, samples are pulled from a depth of 0.5 ft	Guwahati, India	Xiaomi Redmi 3 s Prime
Mengistu and Alemayehu [33]	• Images collected from 3 different cities: Gonder, Metema, Dejen, Addis Ababa • Images clicked in uncontrolled environments therefore contains noise • 6 groups of soil each with 90 images makes 540 total images in the dataset	Addis Ababa, Metema, Dejen, Gonder in Ethiopia	Canon EOS Digital And IP camera
Barman and Choudhury [5]	• 50 soil samples gathered from ten paddy fields with 5 samples from each field • Android phone camera contains a 13-megapixel charged-coupled device	Guwahati, India	Xiaomi Redmi 3 s Prime

6 Performance evaluation metrics

Provided the soil classification approaches, some evaluation metrics of these approaches are significant as they give a merit for the methods applied. Here in this section, a review of evaluation metrics used by the researchers in recent years is discussed. In data classification problems, evaluation metrics can be applied at two stages i.e. training and testing stage. In training stage it is used to optimize the classification process to produce more accurate predictions of the next evaluation and in the testing stage it is used to estimate the effectiveness of the classification technique when unobserved data is fed. In other words, evaluation metrics behaves as a discriminator in order to select the optimum solution in the training stage and behaves as an evaluator to check how much the classifier is efficient in the testing stage.

In binary or multiclass soil classification problems, assessment of the most favorable result at the time of classification can be performed using confusion matrix shown in Table 6. Here, column represents actual class and row represents predicted class. In the matrix, *tp* and *tn* indicate the count of negative and positive examples from the soil image database which are correctly classified. On the other hand, *fp* and *fn* indicate the number of positive and negative examples soil image database which are wrongly classified.

Using this confusion matrix several evaluation metrics can be generated to assess the performance of classifier. Precision (p) is the measure of the positive soil patterns that the classifier predicted correctly out of the entire estimated patterns in a positive class. Recall (r) is the calculation of the ratio of positive soil patterns to the correctly classified soil patters. Accuracy (acc) is the ration of right predictions to the count of examples which were evaluated. F-measure (fm) is the harmonic mean between values of precision and recall.

$$p = \ tp/(tp + fp) \tag{1}$$

$$r = \ tp/(tp + tn) \tag{2}$$

$$acc = \ (tp + tn)/(tp + fp + tn + fn) \tag{3}$$

$$fm = \ (2*p*r)/(p + r) \tag{4}$$

In the supervised learning process, an evaluation metric called Mean square error (MSE) can be calculated during training stage. It calculates the divergence of estimated solutions from the preferred solutions. Value of MSE is needed to be low too achieve a better training performance. It is given as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2 \tag{5}$$

Table 6 Confusion matrix for Soil classification

	Actual positive class	Actual negative class
Predicted positive class	True positive (*tp*)	False negative (*fn*)
Predicted negative class	False positive (*fp*)	Ture negative (*tn*)

Where n is the total number of examples, P_i is the predicted value of example i and A_i is the desired value of example i. It is similar to accuracy as it doesn't give any trade-off information between data classes. The Area under the curve (AUC) is very often use evaluation metric which is used to compare different models and optimize learning models. Basically it provides an overall ranking to the classification technique used is some work. In case of a 2-class issue, AUC can be represented by:

$$AUC = \frac{S_p - n_p(n_n + 1)/2}{n_p n_n} \tag{6}$$

Where n_n and n_p are the count of negative and positive examples respectively whereas S_p is the addition of all the positive examples which were ranked. Even though AUC is acceptable for discrimination and evaluation, its quantification rate is high specifically for multiclass problems. Selection of a proper metric for evaluation and discrimination of the optimal result to get optimized classifier is an important step in soil classification. Suitable selection of metric will lead to a generative type classification along with optimization.

7 Conclusion

In soil classification it is much necessary to reduce human intervention in practice. Day after day demand for food is reaching at its peak and with no execution of modern methods in agriculture, it is very hard to achieve the increasing demands. Deep learning methods are employed for better crop selection based on soil classification. With the help of databases created by researchers and applied to the system, machines communicate among themselves to decide which soil is suitable for a crop. This paper highlights the use of image processing, computer vision, machine learning and deep learning in the field of soil classification. Some of the important characteristics of soil used by the system are color, texture, particle size. These techniques are meant to replace manual inspection of soil.

This paper presented a brief review of soil classification approaches. As described, these approaches can be divided into two groups: image processing and computer vision based soil classification, which consists of four steps, namely, image acquisition, segmentation, feature extraction and soil classification. The classification algorithms used in the approaches include

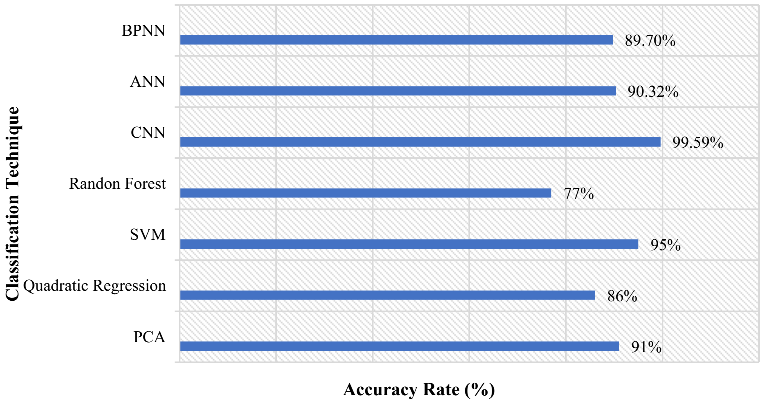

Fig. 12 Comparison of efficiency of Classification Techniques used in soil characterization

random forest, maximum likelihood estimation and k-nearest neighbor. In contrast, deep learning and machine learning based soil classification approaches reduce the dependence on spatial based models and preprocessing methods as it enables end to end learning. However, deep learning based approaches still have few limitations, such as the requirement of large scale datasets, large amount of memory, massive computing power as well as these are time consuming for both training and testing phase. But hybrid approach can show superior performance. Figure 12 shows a Comparison of efficiency of Classification Techniques used in soil characterization and classification studies. This paper also gives a brief review of the databases created by the researchers. In a database, the distance between the soil surface and cameras well as environmental and illumination conditions play important role. Furthermore, evaluation metrics to evaluate soil classification techniques were introduced in order to provide some standard metrics for comparison. This paper also discusses some of the basic and important terminology of soil science. Some of the challenges that would be faced in future by soil classification based on images are:

- There is a requirement of larger dataset of soil images, as the deep learning models work really well on large number of images. The collection of dataset is a challenging task because of the reasons well defined in this paper previously.
- Soil classification system would work well if defined for a selected region. Because the kinds of soil varies from region to region.
- When implying deep neural networks, it have to be kept in mind that it should reduce the cost, storage and time of computation depending on the target users.
- Choosing the correct combination of features (example: color, texture or both), as different objectives are fulfilled by these features. Also, considering color as one of the important feature of soil would be very beneficial.

As far as the future scope is concerned, deep learning techniques are growing at a rapid scale and used in the field of soil classification by employing CNN, RNN or any other computational network. Along with this, massive computing power are needed for training the structure as it becomes increasingly deep.

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Compliance with ethical standards

Declaration of interest The authors declare that they have no conflict of interest.

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