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An Intelligent Model for Indian Soil Classification using various Machine Learning Techniques

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ABSTRACT:On site, soil classification is the need of hour for many geotechnical applications. On-site engineers need some amount of primary information regarding the type and structure of soil. In this paper, the conventional techniques of soil classification are studied and an image processing based efficient classifier for soil classifier has been developed and tested. Seven classes of soil were studied for classification, namely Clay, Clayey Peat, Clayey Sand, Humus Clay, Peat, Sandy Clay and Silty Sand. Reliable images of soils under study were collected and preprocessed. The preprocessed images are feature extracted and the data extracted in used to train the Support Vector Machine (SVM) classifier. The developed classifier is then tested for efficient classification and accuracy for each class is obtained. The developed model can be used in the development of applications for real time soil classification.
KEYWORDS: Soil classification, Image processing, Support Vector Machines, Feature Extraction, Confusion Matrix, Accuracy.

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I. INTRODUCTION

Soil classification is useful in site investigation process as it helps to assess the general suitability of the site for acquire the physical and mechanical properties of soil for adequate and economic design and helps to determine the suitability of materials for construction[1][2]. Indian soils are classified into various groups either on the basis of are where the soil is available or on the basis of the dominating size of particle in the soil[3][4] [5]. On the basis of location, soil is classified as alluvial soil, forest soil, red soil, black/regur soil, arid/ desert soil, peaty/marshy soil and laterite soil, etc. While on the basis of dominating particle size, soil is classified as clay, peat and sand. On the other hand, some soils are classified as mixture of two soils such as Clayey Peat, Clayey Sand, Humus Clay, Sandy Clay and Silty Sand, etc. Another advantage of soil classifications evident from the fact that if an engineer attempts to save the cost with a low budget investigation, then it may cause additional expenditure later if previously undiscoverable unfavorable ground conditions are encountered later. The necessary investigations at site involve laboratory and in-situ techniques. The in-situ techniques may involve exploring the soil properties at the ground level or below the surface. In surface in-situ investigation, geological mapping provides the soil profile while density replacement test tells the measurement of in-situ density of soil. In subsurface tests of in-situ investigation , it in intended to measure certain physical properties or forces of soil such as elasticity, density, magnetic susceptibility, conductivity and moisture evaluation , etc.

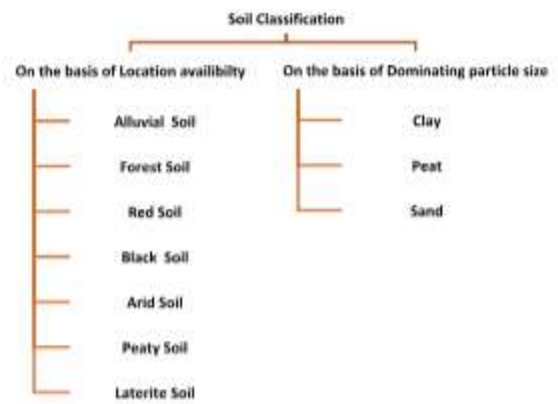

Fig.1 Different type of Indian Soil

Fig. 2 Images of the collected soil samples

Conventional methods of soil classification included manual methods such as Standard Penetration Test (SPT) [6], Cone Penetration Test (CPT) [7], Pressure Meter Test (PMT) [8], and Vane Shear Test (VST)[9]; while some advanced methods included Constraint Clustering and Classification (CONCC) and Boundary energy method. The most recent method of soil classification is by using image processing with the help of SVM classifier [10]. SVM classifier in image processing extracts the features of image and then labels the detected images into separate classes on the basis of similarity of extracted feature from the test image with its training database.

II. RELATED WORK

Prior to the construction of engineering structures, it is required to inspect the site to determine its suitability for the intended structure. The resulted output of this furnished investigation information helps to determine engineering properties of the soil at that specific location.

a. Conventional Techniques To Classify Indian Soil

The conventional techniques of soil classification included Standard Penetration Test (SPT), Cone Penetration Test (CPT), Pressure Meter Test (PMT), and Vane Shear Test (VST), Constraint Clustering and Classification (CONCC) and Boundary energy method. The test results obtained are used to characterize the strength and other properties of the soil at the test location.

i. Standard Penetration Test (SPT)

This form of testing is believed to have evolved from the need to acquire data on subsurface soils. SPT was originally designed for determination of relative density of cohesion less soils. SPT involves the use of cable percussion drilling rig and some accessories. Components used in SPT involve the percussion drilling rig, spit – spoon sampler, hammer and drill rods. SPT characterizes the shear strength of the soil by observing the number of hammer blows required to penetrate to a given depth. In case of soil classification a record is made of the number of blows required to drive 150mm segment into the soil, till 450mm depth [11].

ii. Cone Penetration Test (CPT)

CPT is another in-situ geotechnical investigation technique for soil classification. In this technique, we imply the continuous penetration of rods supported by a cone at a constant speed (20mm/s), while some geotechnical parameters (such as tip resistance, sleeve friction, pore water pressure, etc.) are measured after certain distance interval of penetration. This technique is commonly used to identify near surface unconsolidated soils [12] [13].

iii. Pressure Meter Test (PMT)

A pressure meter is a cylindrical probe that has an expandable flexible membrane designed to apply a uniform pressure to the walls of a borehole. The pressure meter test (PMT) is widely used in weak rocks as an in-situ testing method to determine the stress and deformation relationship of a geo-material [8].

iv. Vane Shear Test (VST)

VST is an economical and fast method for determining the undrained shear strength of soft to medium stiff clays. In VST, four-bladed vane is slowly pushed and constantly rotated into a clay stratum to measure the resisting torque. This method is repeated twice to measure the remolded shear strength. VST has advantages of being an economical, reproducible and fast method. There are chances of error in VST because of excessive rod friction and poor torque calibrations [9].

v. Constraint Clustering and Classification (CONCC)

The CONCC is an algorithm developed to address the shortcomings of previous segmentation algorithms. It is implemented in two steps, segmentation and classification. The CPT data is converted into 'J' segments from a single series of data, and then this data is segmented into classes using a fuzzy logic to address the imprecision in the measured data. For segmentation a concept of boundary energy is applied to parameterize the shape effects.

b. Image Processing Techniques To Classify Soil

i. Basics of Image Processing

Image classification refers to process of labeling the images into one of a number of predefined categories. This type of classification consist of a database that contains the predefined patterns, these patterns are compared with the detected objects to classify the detected object in a proper category. General methodology of image processing describes the steps of image classification as under,

I. Selection of suitable sensor data
II. Selection of classification system and training samples
III. Image preprocessing
IV. Feature extraction and selection
V. Selection of suitable classification method
VI. Post classification processing
VII. Accuracy Assessment

ii). Application of SVM to classify Soil

Support Vector Machine (SVM) is the most successful machine learning technology in pattern recognition and computer vision which is based on statically theory to handle the data efficiently [14] [15][16][17] [18]. SVM's have been widely applied to pattern classification problems and nonlinear regressions by using non parametric classifiers with binary classifier approach. The detailed description of SVM is explained later in this paper. Applications of SVM are found in medical image classification, soil classification and identification, and financial analysis, etc. , as discussed in Table.1, SVM based classification and grading of soil samples using different scientific features is discussed in [19] [20] [21].

In [17] Different algorithms and filters are developed to acquire and process the colored images of the soil samples. These developed algorithms are used to extract different features like color, texture, etc. Different soil types like red, black, clay, alluvial, etc. are considered. In [19], research work involving the use of Matlab program in classification of soil according to AASHTO. The programme does not only classify soil but also give the group index, the general sub-grade rating as well as possible material a particular sample is made of. It also helps in reducing the tedious work of having to go through the chart over and over again. The program has indicated that MATLAB is not only for calculation and analysis but also can be used in analysis involving numeric and word problems simultaneously. In [20], use of Support Vector Machines in the gauge of estimations of soil properties and soil compose order in light of known estimations of specific compound and physical properties in examined profiles is presented. It was seen that for the relapse undertaking, the got results propose that straight techniques are not ready to appraise the estimations of physical properties utilizing the officially estimated compound properties. In any case, the nonlinear SVM can gauge the estimation of dirt and physical sand adequately well. In [22][23],the application of SVM to detect the moisture content in the soil is discussed. In [22], the creator builds up a model is to turn the manual procedure to a product application utilizing picture handling. Picture of the dirt with various dampness content are caught and preprocessed to evacuate the commotion of source picture. The shading and surface characters of damp soil are separated. Shading qualities examined utilizing the RGB and the HSV display. Surface highlights are broke down utilizing entropy, vitality, differentiate, homogeneity. A connection between removed highlights and dampness content is created. In [23], a novel relapse method called Support Vector Machine (SVM) is introduced and connected to soil dampness estimation utilizing remote detecting information. This model is connected to 10 destinations for soil dampness estimation in the Lower Colorado River Basin (LCRB) in the western United States. The precision of the outcomes is by expansive subject to the relationship of the preparation informational collection with the yields for the investigation area; nearness of exceptions and mistaken qualities in the preparation information weakens the model execution. In [24], the applications of SVM to detect soil nutrients are discussed for estimation, detection and comparison of soil nutrient analysis quantitatively by following the principle of chromatography. The original image used in this process is transformed into a polar image using the center of the chromatogram as origin. The application of SVM to detect soil structure is discussed in [23] and applications to detect soil quality are discussed in [26].SVM classifier has also been used to detect pH of the soil using image processing [27] [28] [29] with an objective of making soil testing easy for farmers. In [27], it is examined that dirt shading is visual perceptual property to the classifications i.e. red, green, blue and others, where computerized estimations of red, green and blue (RGB) give some insight for spectral signature catch of various pH in soil. Digital photos were gathered amid daylight while photos of the dirt example were consumed in dull space for the virtue of advanced estimation of the spectra.

ii). Application of ANN to classify Soil

ANN has been used in the field of image processing for classification of texture images [30],prediction of soil profile [31], texture based soil classification [32] ,digital soil mapping [33][34] and soil image modeling [35]. Artificial Neural Networks performance is promising and identifies positive results in soil classification with a high degree of success [36].

III. PROPOSED WORK& METHODOLOGY

In this paper, we describe a proposed system for image classification for soil image which is described in the block diagram. The initial segment is to gather distinctive sorts of soil test picture which is regarded as the selection of suitable sensor data is the first important step in image processing based soil classification as it requires considering factors such as user's need, scale and characteristics of soils under study, the availability of data of soil, cost and time constraints of the study. Different images of soil samples which are to be classified are captured using color camera and are provided as an input to the system. The features of each type of soil are collected and are stored in a separate database. This database is later used in the final stage for soil classification. For successful image classification, a sufficient no. of training samples is required. The training samples are collected from fieldwork. The conditions considered while selecting training samples included spatial resolution of the collected images, availability of ground reference data and complexity of the data being studied.

A. Image Preprocessing

The image acquired from our previous stage is not error free. In order to get an error free image pre-processing techniques are applied. This phase is also known as the enhancement of the image since the image is enhanced by improving its contrast and removing errors to obtain a better quality image for our future processes. The image contains errors like noise or artifacts like scratches, lapping tracks, comet tails, etc which needs to be eliminated before the further processes. Image preprocessing also includes the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration, data conversion among different sources, atmospheric correction (topographic conversion) and quality evolution of data.

B. Feature Extraction

This is the foremost step in this process. All the features that are required for us to classify the soil type are done in this phase. A number of features like the texture, colour, intensity, saturation, hue, etc are extracted for detection of soil type. a filter known as Gabor Filter is implemented for feature extraction. Gabor Filter is a linear filter used for edge detection.Feature extraction included selection of suitable variables which is a critical step for successful implementation of soil image classification task. In this step we select on the variable which are most useful for a particular approach. By the end of this step, a good representative dataset for each class is obtained. It is observed that divergence related algorithms are used to evaluate class seperability and refining training samples for each class. Also other features like entropy, standard deviance, mean, etc.; can be extracted using Gabor filter. The main and important feature of soil that is color is needed to be extracted. Hence a measure called color moments are used to differentiate images based on their features of color. These provide a color similarity between images which can be compared to the values of images indexed in the data base for tasks like image retrieval.

C. Feature Selection

Feature Selection is a dimensionality decrease procedure generally utilized for information mining and learning revelation and it permits end of (superfluous/repetitive) highlights, while holding the hidden unfair data, include determination suggests less information transmission and productive information mining. It additionally brings potential correspondence points of interest as far as bundle crashes, information rate, and storage. The goal of highlight choice is to center around enhancing the expectation execution of the indicators, giving a quicker and more practical indicators and giving a superior comprehension of the fundamental procedure that created the data. There are many element choice strategies, for example, Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA) and Independent Component Analysis (ICA) which factually break down information in the picture to recoup significant examples (relationship and contrast) from picture information to perceive concealed examples to shape comparable class information.

LDA otherwise called Fisher's Discriminant Analysis is a case of a class particular strategy which is dimensionality decrease method. It augments the between – class dissipating lattice measure while limits the inside – class scramble framework measure along these lines making it more solid for characterization.

PCA registers an arrangement of subspace premise vectors for a database of face pictures. These premise vectors are portrayal of pictures which is compare to a face – like structures named Eigen-faces. The projection of pictures in this packed subspace takes into consideration simple correlation of pictures with the pictures from the database. Speculation View of the PCA is known as ICA. It limits the second request and higher request conditions in the information and decides an arrangement of factually autonomous factors or premise vectors. Here we are utilizing engineering I which finds factually autonomous premise pictures.

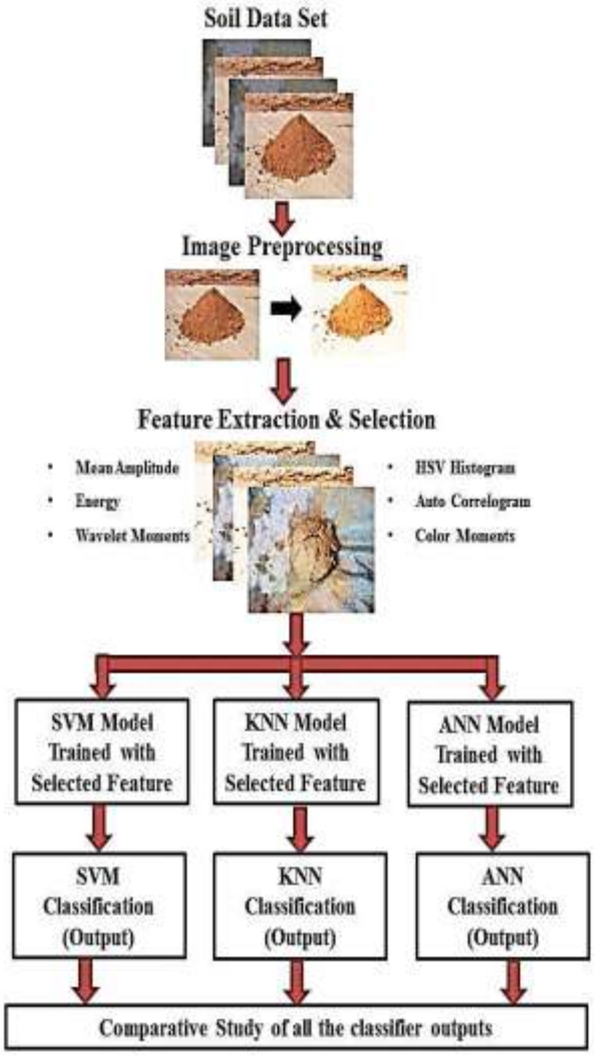

Fig. 2 Flowchart of the Proposed Work

D. Support Vector Machine

Selection of features and classification system is a perquisite for successful classification. Commonly classification systems are designed on the basis of user's needs, spatial resolution of sensed data and algorithms available for preprocessing and classification. SVM is a supervised learning method which generated an input-output mapping function from a set of labeled data. This generated mapping function can either be a classification function or a regression function. SVM plots each feature as a point in n-dimensional space. The ultimate goal of SVM is to design a hyper plane (Decision Boundaries) that classifies the training vectors into two classes. The best choice of the decision boundary being the one which leaves maximum margin from both the classes so as to reduce misclassification in new data.It ability to control over fitting by soft margin separating plane. SVM has various advantages such as : effectiveness in high dimension spaces and the instances where no. of dimensions are greater than no. of samples, availability of different kernel functions for various decision functions, ability to add kernels to achieve complex hyper planes and memory efficiency by using subset of training points.

E. Artificial Neural Network

Artificial Neural Network (ANN) is a figuring models propelled by natural neural system. ANN for normal task problem critical thinking gives new bearings by extracting relevant features from the provided data. ANN performs a pattern recognition task without stating the rules for performing the task. ANN has the capacity to model nonlinear procedures and to recognize obscure examples and pictures in light of their learning model, or to figure certain results by extrapolation. ANN discovers its application in discourse acknowledgment, picture preparing, common dialect handling and basic leadership.

F. K- Nearest Neighbors' Algorithm (k-NN)

K-nearest neighbor algorithm [37] [38] [39] is a method for classifying objects based on closest training examples in the feature space. K-nearest neighbor algorithm is among the simplest of all machine learning algorithms. Training process for this algorithm only consists of storing feature vectors and labels of the training images. In the classification process, the unlabeled query point is simply assigned to the label of its k nearest neighbors. Typically the object is classified based on the labels of its k nearest neighbors by majority vote. If k=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, k must be an odd integer. However, there can still be times when k is an odd integer when performing multiclass classification.

i. Training Part

In the training part, 24 soil sample pictures are collected of two basic soils, Clay and Peat; and five mixed soils, Clayey Peat, Clayey Sand, Humus Clay, Sandy Clay, and Silty Sand as shown in Fig. These soil sample images constructed our training data/ sensed data. The images were taken from an 8MP cellphone camera. After the procurement of the data, a number of preprocesses were applied on the data, one of them being contrast enhancement. For the testing part, a GUI (Graphical User Interface) was developed, which consisted separate buttons for fetching image, enhancing the contrast, displaying the result and accuracy measurement.

ii. Testing Part

As a first step in testing process, the test image if fetched using the 'imread' function. This imported image is then resized using 'imresize' function. After resizing the image if contrast enhanced for efficient feature extraction. This contrast enhanced image is used for extracting features of the test image. The features extracted for this work includes hsvHistogram, color Autocorrelation, color moments, gabor wavelet, wavelet transform. These extracted features are then compiled into a matrix called as 'Feature Vector'. Now the extracted features and training data of soil features from the training part is given to the SVM classifier for assigning the class to the test image.

IV. RESULTS AND DISCUSSION

In this research, the image data of various kinds of soils was collected and compiled. The image data was then decomposed using Discrete Wavelet Transform (DWT) till second level of decomposition using the mother wavelet "daubechies (db)" of DWT. The second decomposed level of data is the input to the next stage of the model i.e. Feature Extraction. A

total of 10 features have been extracted from the decomposed image such as Mean, Standard Deviation, Energy, Entropy, Kurtosis, HSV Histogram, Color Moments, Auto Correlogram, Mean Amplitude, and Wavelet Moments. The six selected features are then given to the various proposed classifier. The proposed selected features have been given to support vector machines to classify the different soil classification. The results of classification accuracy of the SVM with different classifier (namely Linear, Quadratic, Cubic, and Fine, Medium, Coarse Gaussians) function for different cross-fold validation levels are shown in Table 2. It can be seen that the developed method is able to classify the seven type of Indian soil. Therefore, it can be stated that the proposed intelligent soil system is able to classify of seven different types of Indian soils with higher classification accuracy on the experimental dataset.

Table 2: Comparison of classification accuracies of SVM with different classifiers

Cross Fold Validation level	Linear SVM	Quadratic SVM	Cubic SVM	Fine SVM	Medium SVM	Coarse SVM
2	96.8	95.8	94.8	87.5	93.8	93.8
4	99.0	97.9	96.9	88.5	94.8	93.8
6	99.0	96.9	96.9	89.6	93.8	94.8
8	99.0	99.0	99.0	89.6	94.8	92.7
10	99.0	96.9	97.9	87.5	93.8	93.8
12	99.0	95.8	96.9	89.6	93.8	94.8

As a result of comparative study shown in Table 2, it has been concluded that Linear SVM gives best accuracy for all cross fold validation levels.

Table 3: Comparison of classification accuracies of KNN with different classifiers

Crossfolds Validation	Fine KNN	Medium KNN	Coarse KNN	Cosine KNN	Cubic KNN	Weighted KNN
2	94.8	88.5	25.0	90.6	88.5	89.6
4	93.8	90.6	25.0	90.6	89.6	92.7
6	92.7	90.6	25.0	90.6	89.6	93.8
8	93.8	90.6	25.0	90.6	88.5	93.8
10	93.8	88.5	20.8	90.6	88.5	93.8
12	92.7	90.6	25.0	90.6	88.5	93.8

In k- NN different function of k-NN (Fine, Medium, Coarse, Cosine, Cubic, and Weighted k-NN) have been analyzed during this research work and got a good classification accuracy as concluded in Table3 but it has also been observed that the maximum classification accuracy obtained in the case of Fine KNN is less than SVM Classifier.

Finally the ANN has been applied for the soil classification, has got the good classification accuracy as compared with k-NN but less than SVM.

It is observed that from the Table 5, SVM has better classification performance with highest classification accuracy.

It has also been observed that the model developed using SVM can be used for real time soil identification. This model can also be exported to other platforms for other application development works.

Table 4: Comparison of classification accuracies of ANN under different conditions

Fold Cross Validation	Accuracy (%)	Holdout Validation (%)	Accuracy (%)
2	94.2	**15**	96.5
4	93.2	**20**	95.3
6	93.2	**25**	93.2
8	94.2	**30**	92.1
10	90.2	**35**	90.2
12	89.2	**40**	89.2

The comparative study of all the applied classifier has been discussed in Table 5.

Table 5: Comparative study of Linear SVM , Fine KNN and ANN

Cross folds Validation	Linear SVM	Fine KNN	ANN
2	96.8	94.8	94.2
4	99.0	93.8	93.2
6	99.0	92.7	93.2
8	99.0	93.8	94.2
10	99.0	93.8	90.2
12	99.0	92.7	89.2

V. CONCLUSION

On site soil classification is the future research in the field of civil engineering, the concepts of image processing prove efficient for automating this task. In this paper, the task of automation as discussed has been carried out. Seven types of soil data images was collected and processed, further the accuracy data has also been obtained. In this study, it has been observed that the developed SVM classifier can work efficiently with high level of accuracy. MATLAB software has proved an efficient tool for design and development of classifier and can be used for further development of independent interface for on-site real time soil classification.

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