A new deep convolutional neural network technique For image based soil classification

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Abstract: The use of computers in many engineering fields is widely accepted. The field of geotechnical engineering is not far behind. The use of computers not only automates the process of soil characterization, but also makes it more objective. The chances of human error are minimized, thus saving a lot of energy, time and most importantly, money. The present work proposes a new technique to develop a correlation between soil image features and physical properties of soil materials through Digital Image Processing. Classification of soil is the dissolution to soil sets to Particular group having a like characteristics and similar manners. Almost all countries do product exporting, in which Those countries exporting higher agricultural product are very much depend on the soil characteristics. Thus, soil characteristics identification and classification is very much important. Identification of the soil type helps to avoid agricultural product quantity loss. A classification for engineering purpose should be based mainly on mechanical properties. This paper explains support vector machine and CNN based classification of the soil types. Soil classification includes steps like image acquisition, image pre-processing, feature extraction and classification. The texture features of soil images are extracted using the low pass filter, Gabor filter and using colour quantization technique. Artificial neural networks (ANNs) have been widely used for the analysis of remotely sensed imagery. In particular, convolutional neural networks (CNNs) are gaining more and more attention in this field. CNNs have proved to be very effective in areas such as image recognition and classification, especially for the classification of large sets composed by two-dimensional images. The developed techniques include CNN 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. A huge amount of literature is available for soil classification methods using the machine learning methods.

***Index Terms* – Soil classification, Machine Learning, ANN, SVM, CNN, HSV; Gabor filter.**

I. Introduction

Soil is the term which has different meaning for different people: for a geologist it represents the products of past surface processes. To a penologist it represents physical and chemical processes occurring currently. For an engineer soil is the solid thing up on which foundation for houses, factories, building, roads, etc can be built. Soils may be described in different ways by different people for their different purposes. Soil study means the knowing of externally Identifiable patterns seen on soil. Grouping of soil is particularly basic for reasonable agricultural business. Recognizing the characteristics of soil is the key feature to reduce the product quantity losses. It is crucial for countries That export several agricultural commodities. A classification for engineering purposes should be based mainly on mechanical properties, e.g. permeability, stiffness, strength. The class to which a soil belongs can be used in its description. Knowing the type of soil is very useful for cultivation, construction..etc. As far as plant is concerned plantation according to the soil characteristics is very much important for its success. The nature of soil is influenced by many factor, some of them are power of hydrogen (PH), Exchangeable sodium percentage, moisture content…etc. depending on their amount in soil they show different characteristics and that varies for different region. Soil type of a particular geographical area is analysed by collecting samples of soils and classifying them in to different type using different methodologies. In preparation manual segmentation and classification method is monitored. This is time consuming, requires efficient people and expensive also. The main task is to automate the procedure. With the emerging of image processing and machine learning we can efficiently classify the soil sample in to groups which it belong to. This paper describes classification of the found segments using Machine Learning (ML) method Support Vector Machines (SVM) and CNN.

Deep learning-based methods achieve promising performance in many fields. In deep learning, the convolutional neural networks (CNNs) [12] play a dominant role for processing visual-related problems. CNNs are biologically-inspired and multilayer classes of deep learning models that use a single neural network trained end to end from raw image pixel values to classifier outputs. The idea of CNNs was firstly introduced in [13], improved in [14], and refined and simplified in [15, 16]. With the large-scale sources of training data and efficient implementation on GPUs, CNNs have recently outperformed some other conventional methods, even human performance [17], on many vision-related tasks, including image classification [18, 19], object detection [20], scene labelling [21], house number digit classification [22], and face recognition [23]. Besides vision tasks, CNNs have been also applied to other areas, such as speech recognition [24, 25]. The technique has been verified as an effective class of models for understanding visual image content, giving some state-of-the-art results on visual image classification and other visual-related problems. In [26], the authors presented DNN for HSI classification, in which stacked auto encoders (SAEs) were employed to extract discriminative features.

CNNs have been demonstrated to provide even better classification performance than the traditional SVM classifiers [27] and the conventional deep neural networks (DNNs) [18] in visual-related area. However, since CNNs have been only considered on visual-related problems, there are rare literatures on the technique with multiple layers for HSI classification. In this paper, we have found that CNNs can be effectively employed to classify hyperspectral data after building appropriate layer architecture. We present a simple but effective CNN architecture containing five layers with weights for supervised HSI classification. Several experiments demonstrate excellent performance of our proposed method compared to the classic SVM and the conventional deep learning architecture. As far as we know, it is the first time to employ the CNN with multiple layers for HSI classification.

II. SOIL CLASSIFIACTION REVIEW

Development of soil science began with the founding of modern taxonomy of soil, which makes the soil classification and soil science research to become the most classic and basic research category. With the advancement of soil resource mobilization States since the mid-20th century, countries on the basis of their geographical distribution of natural soil use and soil management needs, has formed a plurality of soil classification system which consisted of naming rules that were not consistent, resulting in exchange of scientific aspects of soil processes at the international level, and the lack of common benchmark. Problems begin to arise with the same name, different soil between the so-called different names or different classification systems. In recent years many authors and researchers have engaged in the study of soil survey and soil classification [2]. Soil classification refers to the modern understanding of soil genetic processes on the basis of the different soil classification and naming system. In the mid-20th century to the late half century, the main objective of national soil survey is to identify soil types and their distribution, the main results of the survey are compiled and drawn soil profile blog to complete soil map.In 1883 soil scientist Dokuchaev Russia first proposed the soil zonal doctrine, laid the theoretical foundation of modern soil classification occurred. The core idea of soil genesis taxonomy is that soil classification and naming of the process of formation and iconic characteristics of soil under the influence of climate, biology, topography, parent material, time 5 Dacheng soil factors, so that people identify the different types of soil, nature[3]. Based on soil classification, all major countries in the world have established their own soil classification system based on surface soil sampling survey. Although these classifications are based on the same theoretical basis, but they differ from one another due to the different countries and regions in which the different climatic zones, with the type of soil resources and per capita funding.The amount of different sources, different levels of economic and technological development, using the principles of classification, naming, ground survey methods and sampling volume varies; the final form of the classification system is also different [4].Soil classification system adopted by most countries is described as hierarchical classification (hierarchal system) systems, from high to low, with each level having its own definition of affiliation between the different levels. The soil classification grade classes, and subclasses, for the expression of earth or soil during soil factors form the most significant difference among different soils. The most important feature in advanced classification of different soil types is based on morphological characteristics (morphological feature) which is the difference of the soil structure, mainly refers to the soil type, number, thickness, and material composition of horizons relationship status. As the soil is Classified lower level, for the expression of different soil types soil during soil profile physicochemical difference caused traits, such as texture, clay minerals, ion-exchanged with soil temperature change [5].

III. LITERATURE SURVEY

B.Bhattacharya..etc al.,[3] uses the concept of segmentation , feature extraction and classification. The signals which are measured segmented using segmentation algorithms. Boundary energy method is used for extracting features from the input data. Depending on these features classifiers such as ANN, SVM and decision trees are employed and satisfactory results are obtained. A cone penetration test (CPT) is one among the popular soil investigation method [4]. It is used for modelling the sub-surface soil and for a little depth information gathering from collected soil samples.

A constraint limits the solutions available. The paper[6] gives a survey on constrained classification. the paper handles with various algorithm on classification, properties of classes on division and the topologies of decision tree diagrams. The paper uses few parameters for representing complex geological models using principle component analysis (PCA). Normal PCA works by performing multiplication using basis matrix and makes high dimensional model. Here optimization is used for mapping (O-PCA) which have non-Gaussian characteristics and enhance the features. Thus it is used for reducing gradient based approaches and to improve the matching process [8].

A Comprehensive Foundation on neural networks [7] provides an inclusive overview on the neural network applications. An overview in knowledge illustration along with in what way they are used in artificial intelligence (AI) is given. The vapnik-chervonenkis (VC) dimension is explained here with respect to the training samples that a machine can absorb without errors. This contains information about the least mean square error, back propagation. Fuzzy measure is used as base for aggregating the correlation between relative densities and CPT. Here three levels high, low, medium sands are selected by friction ratio. Based on the differences between these levels the compressibility is measured. Based on fuzzy c-means and integrals the correlation density is measured. Obtained results are compared here [10]. Decoding of Bose Chaudhuri Hocquenghem codes (BCH) is explained using multiclass SVM. Normal algorithm the decoding is fixed regardless of the SNR environment. Thaw there is no local minima and outlier robust SVM shows a great capacity in decoding the BCH codes [1]. ABDF is feature enriched and helpful and provides GUI for examine the huge data. [2] Zhongjie Zhang..etc..al., the paper explains that there will be an uncertainty between the soil composition correlation and mechanical behavior of soil while deriving from CPT. This uncertainty leads to overlapping of different soil classes. The existing method available for this is point and region estimation. The author introduces a new fuzzy approach here that is independent of CPT [22].

I.T. Young..etc..al, [21] introduces a concept for analyzing the technique for biological shape based on bending energy. It finds out the amount of work used for typical biological shape in addition to this it explains sampling theorem for contours which are connected and closed and a fast algorithm for calculating the bending energy. R. Webster ..etc al., introduces two method in Optimally partitioning soil transects[19]. One method is by using a window called split moving window (SMW) and the other one is maximum level variance (MLV). The transect is examined through the SMW and the values on the other side of the mid-point is compared. MLV do examines each and every possible regions thus minimizing the within square variance. A comparisons and calculation of these methods is summarized over here.

IV. CNN-Based HSI Classification

1. Applying CNNs to HSI Classification

The hierarchical architecture of CNNs is gradually proved to be the most efficient and successful way to learn visual representations. The fundamental challenge in such visual tasks is to model the intraclass appearance and shape variation of objects. The hyperspectral data with hundreds of spectral channels can be illustrated as 2D curves (1D array) as shown in Figure 2 (9 classes are selected from the University of Pavia data set). We can see that the curve of each class has its own visual shape which is different from other classes, although it is relatively difficult to distinguish some classes with human eye (e.g., gravel and self-blocking bricks). We know that CNNs can achieve competitive and even better performance than human being in some visual problems, and its capability inspires us to study the possibility of applying CNNs for HSI classification using the spectral signatures.

2. Architecture of the Proposed CNN Classifier

The CNN varies in how the convolutional and max pooling layers are realized and how the nets are trained. As illustrated in Figure 3, the net contains five layers with weights, including the input layer, the convolutional layer C1, the max pooling layer M2, the full connection layer F3, and the output layer. Assuming represents all the trainable parameters (weight values), and where is the parameter set between the $\theta = \{\theta_i\}$ and $i = 1, 2, 3, 4$, where θi is the parameter set between the $(i - 1)$th and the ith layer. The input represents a pixel spectral vector, followed by a convolution layer and a max pooling layer in turns to compute a set of 20 feature maps classified with a fully connected network.

In HSI, each HSI pixel sample can be regarded as a 2D image whose height is equal to 1 (as 1D audio inputs in speech recognition). Therefore, the size of the input layer is just and is the number of bands. The first hidden convolutional layer C1 filters the input data with 20 kernels of size. Layer C1 contains nodes. There are trainable parameters between layer C1 and the input layer. The max pooling layer M2 is the second hidden layer, and the kernel size is . Layer M2 contains nodes there is no parameter in this layer. The fully connected layer F3 has nodes and there are trainable parameters between this layer and layer M2. The output layer has nodes, and there are trainable parameters between this layer and layer F3. Therefore, the architecture of our proposed CNN classifier totally has trainable parameters. Classifying a specified HSI pixel requires the corresponding CNN with the aforementioned parameters, where and are the spectral channel size and the number of output classes of the data set, respectively. In our experiments, is better to be and can be any number between 30 and 40, and . is set to be 100. These choices might not be the best but are effective for general HSI data.

V. DATASET

Three hyperspectral data, including Indian Pines, Salinas, and University of Pavia scenes, are employed to evaluate the effectiveness of the proposed method. For all the data, we randomly select 200 labelled pixels per class for training and all other pixels in the ground truth map for test. Development data are derived from the available training data by further dividing them into training and testing samples for tuning the parameters of the proposed CNN classifier
The dataset consisted of a collection of 175 soil sample measures.

Fig 1: Clay

Fig 2: Clayey Peat

Fig 3: Clay Sand

Fig 4: Humus Clay

Fig 5: Peat

Fig 6: Sandy Clay

Fig 7: Silt Sand

VI. EXPERIMENTL RESULTS

The system recognizes and classifies different type of soils like the result as Below is a summary of the metrics we adopted to evaluate the detection method:

	Predicted: Sandy Soil	Predicted: Non-Sandy Soil
Sandy Soil	TN	FP
Non - Sandy Soil	FN	TP

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$DR = \frac{TP}{TP + FN}$$

$$FAR = \frac{FP}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{(TP + FN)}$$

where, accuracy (*ACC*) is the percentage of true detection over total data instances; detection rate (*DR*) represents ratio of intrusion instances; false alarm rate (*FAR*) represents the ratio of misclassified normal instances; *Precision* represents how many of the returned attacks are correct; *Recall* represents how many of the attacks does the model return. *FP*: false positive, *TP*: true positive, *TN*: true negative, *FN*: false negative.

SVM	*ACC*	*DR*	*FAR*	*Precision*	*Recall*
Sandy Soil	94.34	93.80	0.80	99.20	99.70
Non - Sandy Soil	94.57	94.40	0.85	99.30	99.41

CNN	*ACC*	*DR*	*FAR*	*Precision*	*Recall*
Sandy Soil	95.42	94.85	0.98	99.45	99.74
Non - Sandy Soil	95.68	95.45	1.25	99.58	99.81

VII. CONCLUSION

We proposed a novel CNN-based method for HSI classification, inspired by our observation that HSI classification can be implemented via human vision. Compared with SVM-based classifier and conventional CNN-based classifier, the proposed method could achieve higher accuracy using all the experimental data sets, even with a small number of training samples.

Our work is an exploration of using CNNs for HSI classification and has excellent performance. The architecture of our proposed CNN classifier only contains one convolutional layer and one fully connected layer, due to the small number of training samples. In the future, a network architecture called a Siamese Network [33] might be used, which has been proved to be robust in the situation where the number of training samples per category is small. Some techniques, such as Dropout [34], can also be used to alleviate the overfitting problem caused by limited training samples. Furthermore, recent researches in deep learning have indicated that unsupervised learning can be employed to train CNNs, reducing the requirement of labelled samples significantly. Deep learning, especially deep CNNs, should have great potentiality for HSI classification in the future. Moreover, in the current work, we do not consider the spatial correlation and only concentrate on the spectral signatures. We believe that some spatial-spectral techniques also can be applied to further improve the CNN-based classification. At last, we plan to employ efficient deep CNN frameworks, such as Caffey, to improve our computing performance.

In this project we have correlated the experimentally determined laboratory results with the RGB value. The RGB value of an image is so extracted that each pixel RGB value is calculated and in which most common RGB values of the image is correlated with the laboratory results considering that the most part of the image is covered by soil particles so that the most common RGB value is the RGB value of the soil particles of the image. The final results of this project will contribute to make soil physical properties estimation automatic up to a certain degree of level, which will assist to a geotechnical engineer, in soil classification. The project has been finally programmed using Python so that the procedure to get the results over the soil is made user friendly & more easily available by a single click

VIII. FUTURE SCOPE

A future study on soil properties can be done by increasing more number of images on same soil & an interpolation type of correlation can be given.

Since water content is one of the factors affecting the color of soil, index tabulation can be made between the image and their RGB values with varying water content of same type of soil sample.

In our project we have just correlated the results of grain size distribution obtained in the laboratory experiment instead that a programming can be done before correlating the results with RGB value to get accurate results on Grain size analysis by Image particle analysis.

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