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ANALYZING AND IDENTIFYING SOIL TYPES THROUGH IMAGE PROCESSING BASED ON TEXTUAL AND GLOBAL FEATURES

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Abstract

Agriculture stands as a vital pillar for human survival on Earth. However, agricultural land is dwindling as the population continues to grow. Fortunately, advancements in technology have led to increased production despite this decline in available land. Onsite 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: Agriculture, Land type, SVM technique, Image processing, classification technique

1. INTRODUCTION

Agricultural production has been highly dependent on natural resources for centuries. The maintenance of good soil quality is vital for the environmental and economic sustainability of annual cropping. A decline in soil quality has a marked impact on plant growth and yield, grain quality, production costs and the increased risk of soil erosion [1]. The field of Computer vision and digital image processing (DIP) is continuously evolving and is finding many applications in several fields. Soil classification and characterization is an important aspect of geotechnical engineering which has been given a great amount of attention since the past few years. The goal of soil micro morphology, as a branch of soil science, is the description, interpretation, and measurement of components, features, and fabrics in soils at a microscopic level.

The soil is a mixture that contains minerals, organic matter, and living organisms. It consists of inorganic particles and organic matter. Soil provides the structural support to plants used in agriculture and is also their source of water and nutrients. Soil is one of the earth's most important natural resources. It underpins human food production systems, supports the cultivation of vegetation for feed, fiber and fuel, and has the potential to help combat and mitigate climate change.

The major steps of image classification may include determination of a suitable classification system, selection of training samples, image preprocessing, and feature extraction and selection of suitable classification approaches. Supervised Classification techniques require training areas to be defined by the analyst in order to determine the characteristics of each category. Unsupervised Classification searches for natural groups of pixels, called clusters, present within the data by means of assessing the relative locations of the pixels in the feature space. Hybrid Classification: It takes the advantage of both the supervised classification and unsupervised classification. These classifiers are generally characterized by having an explicit underlying probability model, which provides a probability of being in each class rather than simply a classification. The performance of this type of classifier depends on how well the data match the pre-defined model. The composition of the system is made of five sections namely soil testing, image capturing, image processing, training system for neural network, and result. The use of Artificial Neural Network is to hasten the performance of image processing in giving accurate results. The system will be based on captured image data, 70% for training, 15% for testing and 15% for validation as the default neural network tool of MATLAB. Based on the result, the program will show the qualitative level of soil nutrients and pH. Overall, this study identifies the soil nutrient and pH level of the soil and was proven accurate.

2. LITERATURE SURVEY

[4]Umesh Kamble and et al in 2017 has classify the soil using image processing based on PH value. So, they classify the soil whether soil is acidic, alkali and neutral. This type of classification is not useful for farmers because farmers cannot understand it easily

[5]. Bhawna J. Chilke and et al in 2017 has find PH value of the soil using image processing But there were difference between experimental test result and automated test result using digital image processing

[6]. Sudhir .R and et al in 2017 has also determined PH value of the soil using image processing. They used the images taken by GIS system [3]. V. Rajeshwari and K. Arunesh in 2016 analysed soil and also classify the soil but using data mining technique. They also done the comparative analysis for accuracy using JRip, J48 and Naïve Bayes algorithm

3. EXISTING SYSTEM

Soil is the layer of the earth surface. That constructed due to broken down of rocks and decaying of animals and plant life. Soil is basically two type, local soil and transportation soil. it was implemented an algorithm for disease spot segmentation using image processing techniques in plant leaf. Considering that disease spots are different in colour but not in intensity, compared with plant leaf colour, the authors used colour analysis of the RGB image to identify the affected plants. For image smoothing was used a median filter and finally threshold was calculated by applying GLCM method on colour component to detect the disease spot The used technique consists in the capture of maize leaf image and preprocess it, for removing the noise of source image. After that, the colour and texture characters are extracted and using the RGB and the HSV model the colour characteristics are analyzed. Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since they were proposed. To many image analysts, they are a button you push in the software that yields a band whose use improves classification This document concerns some of the most commonly used texture measures, those derived from the Grey Level Co-occurrence Matrix (GLCM). The essence understands the calculations and how to do them. This involves

- Defining a Grey Level Co-occurrence Matrix (GLCM)
- Creating a GLCM
- Using it to calculate texture in the exercises.
- Understanding how calculations are used to build up a texture image
- Viewing examples of the texture images created with various input parameters

There has been some recent development of a more efficient way to calculate third-order textures. The third group of GLCM texture measures consists of statistics derived from the GLC matrix. These are

- GLCM Mean,
- GLCM Variance (or Standard Deviation) and
- GLCM Correlation.

Similar statistics derived from the GL values in the original image (not the GLCM) are also used as indicators of texture, but not of GLCM texture.

DRAW BACKS:

1) Does Not Find Out rock and soil mass classification
2) Large Training Data Requirements: perform best when trained on a large and representative dataset. Collecting and labeling a comprehensive dataset for soil texture classification can be time-consuming and expensive.

4. PROPOSED SYSTEM

This project is intended to support agriculture by classifying 7 different types of soils like Clay, Clayey Peat, Clayey Sand, Humus Clay, Peat, Sandy Clay and Silty Sand, and in suggesting suitable crops that could be grown in those particular soils using image processing. Pre-

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processing is done by using Low Pass filter. HSV, GLCM, Gabor Wavelet algorithms are used for feature extraction. HSV, colour based feature extraction. Gabor filters are used to perform texture based feature extraction. The features obtained from the test image are then compared with the features obtained from the images in the dataset. Matching of image features is achieved by training the Decision Tree classifier with statistical measurements like mean, standard deviation, skew and kurtosis. Finally the soil is predicted The existing method of soil classification and crop suggestion require manual involvement, human errors, and the results are uncertain. The method is also time consuming and invasive in nature. But our proposed system overcomes all these errors because it takes into account the physical properties of soil for classification and prediction.

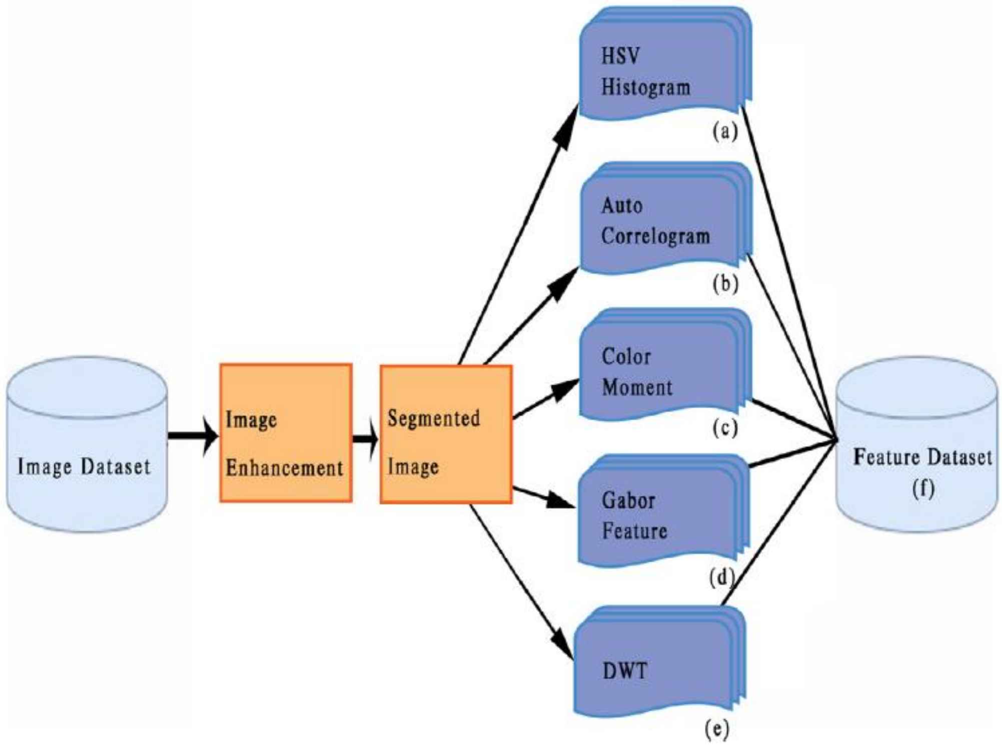

Fig 4.1 : Proposed System For Soil Detection

4.1 METHODOLOGY

Following are the various levels involved in image processing: 1. Low level processing 2. Medium level processing 3. High level processing

- Low level processing (LLP): It involves image enhancement, removes noise using Gabor filter and resizes the image.
- Medium level processing (MLP): It involves image segmentation and classification.
- High level processing (HLP): It involves image identification.

Filtration: Filtration in our proposed system is done using Low Pass filter. Low Pass filter is used to pass signals with frequency lower than the cut-off frequency and attenuates all other signals with frequencies greater than the cut-off frequency. In our proposed system Low Pass filter is used to remove unwanted components and features from the signals so as to reduce noise in the signal. Low Pass filter is also used for shade correction, even brightening and for removing artifacts.

Feature Extraction: Features are the fundamental components of an object. It is used to distinguish one object from the other. Features are also referred to as descriptors. The process of obtaining features from an object is known as description of an object. In our proposed system feature extraction is done by two methods

1. Colour based feature extraction
2. Texture based feature extraction

1.Colour Based Feature Extraction: Hue Saturation Value (HSV), Gray Level Co-occurrence Matrix (GLCM) are used for Colour based feature extraction in our proposed system. The existing system used few tests including Cone Penetration Test (CPT), Vane Shear Test (VST), Standard Penetration Test (SPT), Pressure Meter Test (PMT). But our proposed techniques are used to extract necessary features so as to suggest crops and the accuracy exceeds the bar which was set by the existing tests.

Hue Saturation Value (HSV): Using this model, an object with a specific color can be detected and tthe influence of light intensity from the outside is reduced.

Gray Level Co-occurrence Matrix (GLCM): Given an image composed of pixels, each with an intensity (a specific gray level), the GLCM is a tabulation of, how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity.

2.Texture Based Feature Extraction: Gabor Wavelet Technique: These are wavelets invented by Dennis Gabor using complex functions constructed to serve as a basis for Fourier transforms in information theory applications. The important property of the wavelet is that it minimizes the product of its standard deviations in the time and frequency domain.

4.2 Classification: Classification is based on features of image and category of organized data. Basically classification method has two phases:

- Training phase
- Testing phase

Types of classification: Supervised classification Unsupervised classification. Statically process

Classification is the process of categorization, we apply some classification algorithm to classify different types of fruit .SVM can be used. If we drew a perpendicular line from each point to the

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regression line, and took the intersection of those lines as the approximation of the original data point, we would have a reduced representation of the original data that captures as much of the original variation as possible. Notice that there is a second regression line, perpendicular to the first, shown in Figure 4.2.

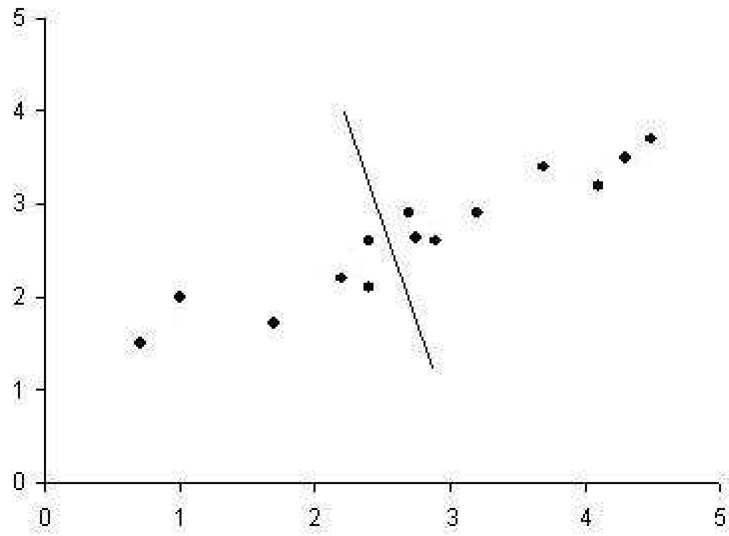

Fig 4.2: Regression line along second dimension captures less variation in original data.

4.3 Accuracy for multi SVM

The soils are classified using SVM with a kernel function. A kernel is a similarity function and it takes two inputs and spits out how similar they are. In this paper SVM with a linear kernel is applied to classify the soil classes

5. RESULTS AND DISCUSSION

The image data of various kinds of soils was collected and compiled. The category of the soil is identified and the name is displayed in a dialogue box. And also a GUI is generated which shows the features, i.e., HSV list, Auto Correlation, Color Moments, Mean Amplitude, Energy, Wavelet Moments along with the accuracy and category of the soil. The proposed features have been given to the Modified support vector machines to classify the soils.

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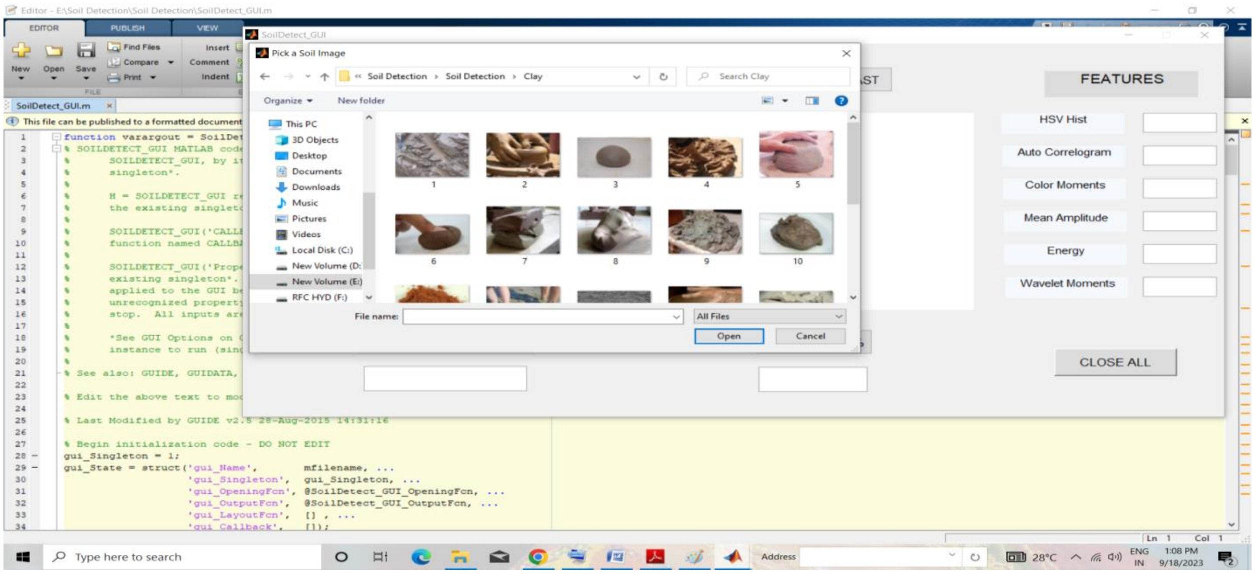

Fig 5.1: Browse the Input Image

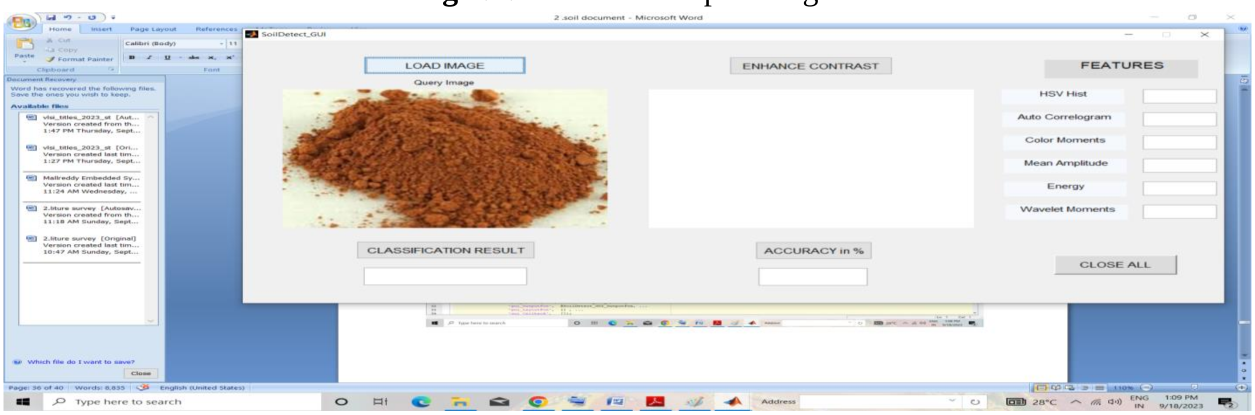

Fig 5.2: Load The Query Clay Image

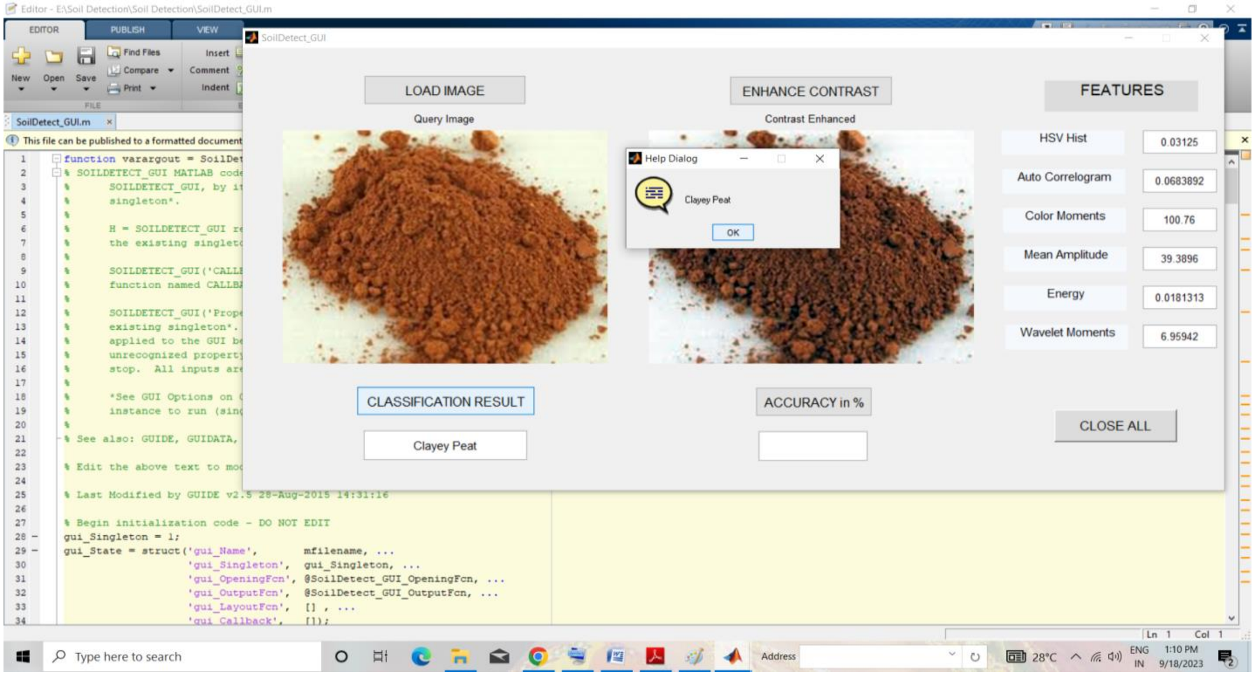

Fig 5.3: Output Of Classified Clay Image

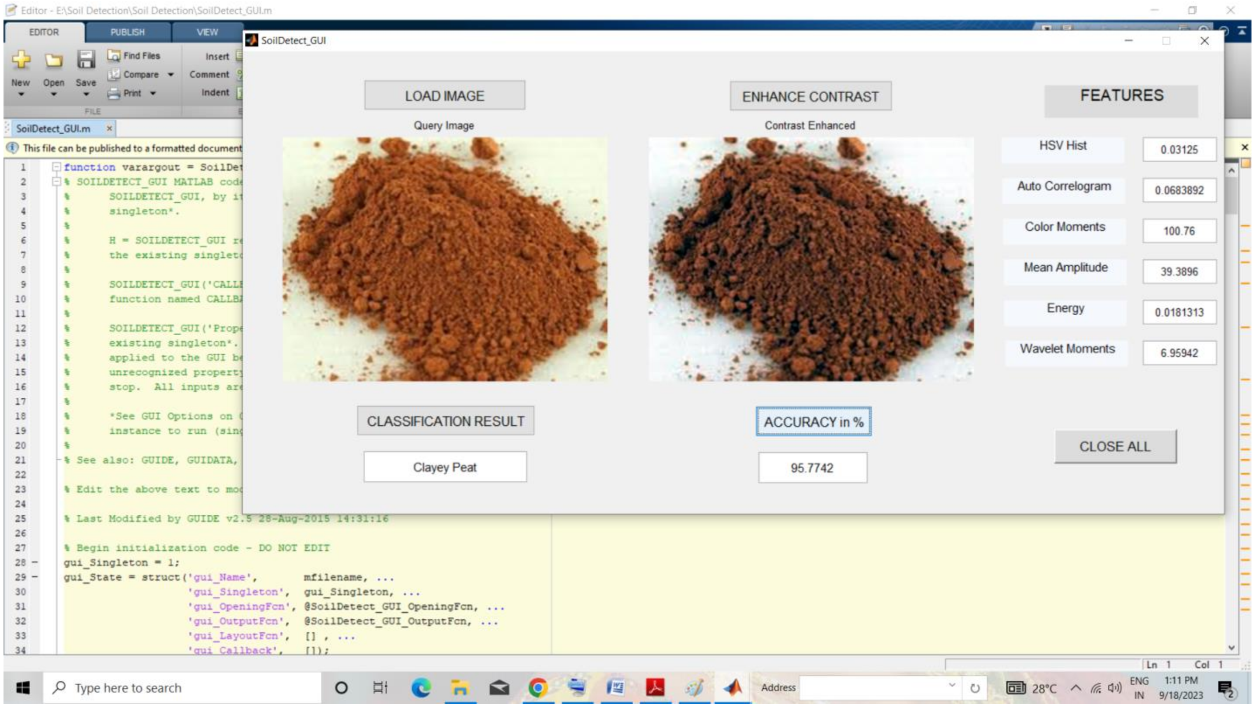

Fig 5.4: The Simulation Result Is Given As Accuracy Is 95.7742%

6. CONCLUSION

The proposed system has added features like crop suggestion, prediction of water absorption by plants which couldn't be found in existing systems. Accuracy is more because feature extraction is based on colour and texture of the input images. Thus our proposed idea will make sure to help farmers, agriculture has more features then the existing system like nutrients of soil, suggested crop list and suggested urea. These features are necessary for the laymen farmers because these are useful in farming and can be understand easily. In this paper, an image based texture analysis is presented to classify the soil images using multi SVM and linear kernel function. The images are captured using android mobile phone camera. The three class classifier and multi-class classifier gives a good performance for the real dataset

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