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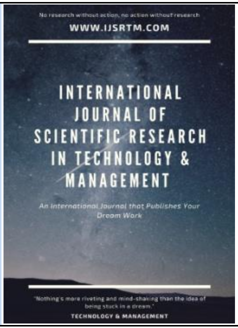

Automatic Soil Classification using Polynomial Support Vector Machine

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Abstract*— Soil classification is an approach that can classifies the soil on the basis of its texture. Geographically there are various types of soil present in the earth that can be classified on the basis of its patterns and physical characteristics. There are various combinations of soil properties available such as- its structure, color, texture and porosity. In machine learning approaches; machines target these factors and train the model accordingly to classify the soil type. Many of the systems are based on machine learning approaches where they use deep neural networks. But the problem with the deep neural network is that if utilized network has been not used then weight of the network might be bulky that increase the size of the network and system get slower to execute and training and testing may take long time. The proposed system is based on polynomial support vector machine (P-SVM) that can classify the soil by dealing with its non-linear textures or data. SVM has great potential to classify the grouped cluster on the basis of their patterns. Patterns are the feature mapping that may belong from different particles. For other classification algorithm; it is difficult to draw a hyper plane for non-linear data but SVM can classifies the data by transforming it to the linear data and then hyper plane can be drawn easily. It has been managed through kernel trick where high dimensional feature space can be mapped. SVM can also solve the optimization problem by utilizing its polynomial feature. System perceived high level of accuracy as compare to the previous model. System pertained __ percent of accuracy.

***Keywords*— Soil Classification, Soil Identification, Image Processing, Textural Data, Soil Analysis, Feature Extraction, Clustering.**

I. INTRODUCTION

Soil is the loose surface material that covers most land. It includes inorganic particles and regular matter. Soil offers the essential assistance to plants used in agribusiness and is also their wellspring of water and enhancements. Soils vacillate amazingly in their manufactured and real properties. Classifying soil is in staggering interest as it helps with investigating the site and gives significant information about the materials Soils are organized ward on different properties, it might be founded on the spot and in view of the size of particles in it. We can bunch soil here in light of the spot and surface. Standard method for soil classification like squeezing factor meter test, vane shear test are somewhat monotonous. There is a urgent need of robotization in this field likewise so we in this adventure frame about the use of picture planning techniques for classifying soil. Soil classification is the division of soil into classes or gatherings each having comparable attributes and possibly comparative way of behaving. A classification for the end goal of designing ought to be founded principally on mechanical properties, for example porousness, solidness, strength. Here the framework depends on Histogram Equalization and Support Vector Machine that upgrade and orders the soil at its best degrees.

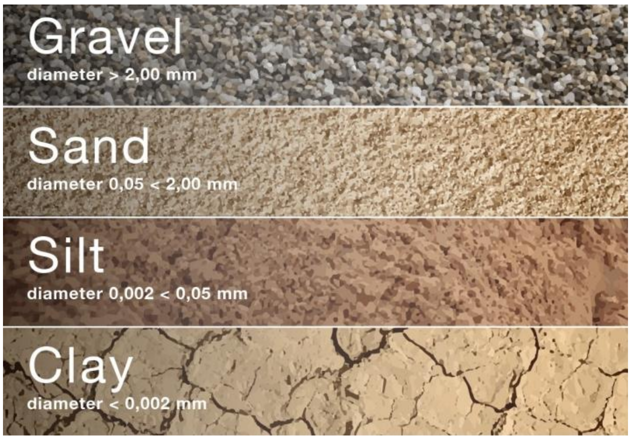


Fig. 1. Soil Textures [2]

Framework obtained better precision alongside various soil highlight portrayals. The general accuracy is superior to the all recently executed frameworks. Irrefutable explanation land is a critical asset and a method for supporting position.

It is the unmistakable advantage for most human activities including officer administration, cultivating, industry, mining, etc Land is essential component of creation solidly associated with the monetary improvement of a nation and its family, in any case, as the general population constructs, interest for land for use in repayment, advancement of structure, developing and other human activities moreover augments. Actually the use of soil classification has procured and more importance and continuous heading in research works exhibits that image classification of pictures for soil information is the leaned toward choice [1]. Various methodologies for image classification have been made ward on different theories or models. MLC and SVM are hard classification strategies anyway SP is a fragile classification. Hardening of fragile classifications for accuracy eads to loss of information and the precision may unreasonable location the strength of class support. As such, in the assessment of the methodologies, the top 20% manifestations per soil class of the SP were used taking everything into account. Results from the dicated that yield from SP was overall poor disregarding the way that it performs well with soils, for instance, forest that are homogeneous in character [1]. Of the two hard classifiers, SVM gave an unrivaled yield Soil Classification, image processing, It's everything except a conspicuous decree that 'land is a huge asset and a method for supporting position'. It is the unmistakable benefit for most human activities including officer administration, agribusiness, industry, mining, etc Land is thusly a chief element of creation immovably associated with the financial improvement of a nation and its kin. Anyway, as the general population grows, interest for settlement, advancement of system, developing (agriculture) and other human activities also increases. Satisfying accordingly, land and its connected ordinary resources like forest area, vegetation, etc are being mistreated unendingly to changes and t turns impact the organic framework. To be sure, even water resources like streams, streams and wetlands that may be found in districts where such activities happen are moreover affected. For example, when changes occur in vegetation; untamed life climate, fire conditions; a genuine characteristics and encompassing air quality, are completely impacted. As human and typical powers are changing the scene, resource workplaces find it continuously crucial for screen and assess these changes. Land use and soil is consequently most huge element of natural change like deforestation, living space brokenness, urbanization, and wetland debasement. Soil deals with the real features or vegetation as clear on the land while land use is about what monetary development or use the land is placed to Exploration in land use.

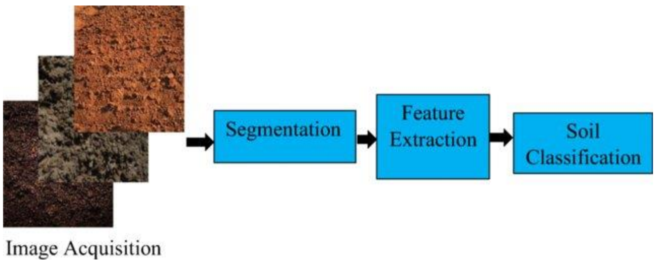


Fig. 2. Soil Classification Steps

Fig. 2 shows the traditional method of extracting textures or features of the soil and step including in classification. Soil considers have made such a ton of interest locally and generally in light of worries overall shorewards use. Soil changes and its results to the environment. It has hence gotten one of the basic parts in pictures classification for coherent assessment and authentic topography applications fundamentals required for such examinations are Different procedures are used for the making of these aides, regardless, the use of far away distinguishing for map creation is growing become the reasonably humble and quick technique for acquiring up information over a gigantic geographical district. Image processing is a field where object can be classified as per its appearance or features on it. Soil can be classified by using image processing tools with high accuracy. Image is a two dimensional signal with having X and Y coordinates. The coordinates represent the location of the pixel of textures present in the image. There are several approaches have been adopted to identify or classify the soil whether it is clay, clay peat, slit, sandy and many more [3]. There is a necessity of computer vision based soil classification procedures which will help ranchers in the field through which they can deal with the time. This paper discusses different computer vision based soil classification rehearses partitioned into two streams. First is image handling and computer vision based soil classification approaches which incorporate the regular image handling calculations and techniques to group soil utilizing various highlights like surface, shading, and molecule size. Second is deep learning and machine learning based soil classification draws near, for example, CNN, which yields classifying edge outcomes. Deep learning applications for the most part lessen the reliance on spatial-structure plans and preprocessing procedures by working with the start to finish process. This paper likewise presents a few information bases made by the specialists as per the target of the review. Information bases are made under various ecological and enlightenment conditions, utilizing various apparatuses like computerized cameras. Likewise, assessment measurements are momentarily examined to design a few evaluated measures for separation. This audit fills in as a short manual for new analysts in the field of soil classification, it gives essential agreement and general information on the advanced feature explores, notwithstanding capable scientists thinking about a few powerful patterns for future work.

II. Literature Review

A. Related Works

This section is intended to review various researches and their results and identify certain common problem findings with them. System's precision is often significant because precise classification and identification can help the agribusiness organizations and individuals. However, many examinations have assessed the precision and consistency of the soil classification using various techniques. This examination starts by evaluating the verifiable advancement of soil classification science. The verifiable audit contextualizes the wordings and the speculations of soil development factors, which supported soil classification frameworks. This paper is intended to review some research papers on soil classification and analyze the limitations of implemented techniques by their parameters. In the age of digital world, it is beneficial to obtain the information from image without any hassle. Shraddha Shivhare et al. [4] implemented a system which is based on Gabor Wavelet and Support Vector Machine. Author uses conventional support vector machine for classifying the soil images. System also uses Gabor Wavelet for extracting the texture of the image and process accordingly. System targeted 7 categories of soil and classified with each 11 trails along with 500 iterations. But conventional SVM is not effective the non-linear data that may produce incorrect recognitions. Vijay E V et al. [5] implemented a system that is based on Support Vector Machine. The image processing ideas are demonstrated as effective techniques for mechanizing this errand. Various calculations exist for soil classification yet soil classification with high exactness and with less consumption is testing process. In this paper, the computerization is proceeded according to the system. Here seven unique classes of soil were thought of and these soils were handled. Furthermore the exactness is additionally determined. In this paper, it is seen that Modified Support Vector Machine can work in a productive way with better precision level. R. Pittman, B. Hu et al. [6] introduced a system that is based on LIDAR data. The natural covariates of CHM and hole division, each got from LiDAR information, were of high factor significance when contrasted with other ecological covariates for soil surface classification. CHM had the most noteworthy variable significance of 7.77 % IncMSE among a bunch of 104 covariates, and hole part was as yet in the top indicators with 2.35 % IncMSE for variable significance. The extents of the variable significance values expanded for CHM and hole part for the diminished arrangement of covariates considered significant for the soil surface displaying. Hement Kumar et al. [7] implemented a system that is based on conventional SVM. The features are fundamental for the laymen farmers considering the way that these are important in developing and can be see with next to no issue. The proposed application has more highlights then the current framework like supplements of soil, recommended crop list and proposed urea. These highlights are vital for the laymen ranchers on the grounds that these are helpful in cultivating and can be see without any problem.

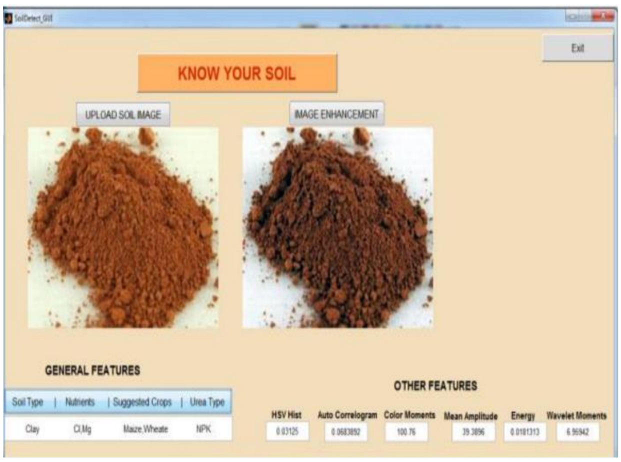


Fig. 3. HSV & Linear SVM based Soil Classification [7]

A. V. Deorankar et al. [8] performed an analytical approach for soil classification in the field of machine learning. This paper studies the various calculations and techniques related with the land classification and in this paper, it has been endeavored to recognize a strategy for identifying the supplement level in the soil. Natural matters assume a fundamental part in soil wellbeing. B. Bhattacharya et al. [9] proposed a procedure for computerizing this classification framework is presented. At first, a division estimation is made and applied to area the intentional signs. Likewise, the striking features of these areas are taken out using limit energy strategy. Taking into account the purposeful data and eliminated features to designate classes to the sections classifiers are created; they use Choice Trees, ANN and Support Vector Machines. The method was attempted in requesting sub-surface soil using assessed data from Cone Infiltration Testing and adequate results were gained. Pramudyana Agus Harlianto et al. [10] proposed a Machine learning computation that can be applied for automating soil type classification. This paper takes a gander at a couple of machine learning estimations for organizing soil type. Computations that incorporate support vector machine (SVM), neural organization, decision tree, and unsophisticated bayesian are proposed and studied for this classification. Soil dataset is taken from the veritable data. Amusement is constrained by using Rapid Miner Studio. The show saw is the precision. The result shows that SVM, with the usage of straight limit bit, beats the others computations. The SVM best precision is 82.35%. P.Bhargavi et al. [11] proposed a utilization of a genetic programming system for classification of decision tree of Soil data to orchestrate soil surface. The data base contains assessments of soil profile data. They have applied GATree for creating classification decision tree. GATree is a decision tree producer that relies upon Hereditary Calculations (GAs). In this paper soil plan is performed using GATree, which is a decision tree designer that relies upon Hereditary Calculations (GAs). The idea behind it is genuinely clear anyway astonishing. Rather than using estimation estimations that are uneven towards unequivocal trees we use a more versatile, overall estimation of tree quality that endeavor to smooth out precision and size. Sk Al Zaminur Rahman et al. [12] proposed a model for expecting soil plan and giving suitable reap yield thought to that specific soil. The assessment has been done on soil datasets of six upazillas of Khulna area. The model has been attempted by applying different sorts of machine learning estimation. Stashed tree and K-NN shows incredible precision anyway among all of the classifiers, SVM has given the most significant accuracy in soil classification. The proposed model is legitimized by a fittingly made dataset and machine learning computations. The soil classification accuracy and besides the idea of yields for express soil are more fitting than many existing methods. M van Rooyen, N Luwes et al. [13] proposed classification of dynamic soils is a basic part in primary planning adventures. There is a necessity for more exact techniques for classification. This paper surveys a handmade machine vision classification system. From composing review, Stokes' regulation was recognized as a likely approach for the machine vision system. Stirs up's states that the estimation squared of a particle is clearly comparative with the settling velocity of the atom in a fluid. This paper evaluates in the event that a power histogram can be used as a marker of settling speed. While building the computerized soil classification structure using machine vision it is basic to control the lighting whatever amount as could be anticipated.

Table No. I Problem Findings & Comparison

Author/s	Method	Findings	Accuracy
Shraddha Shivhare et al. [4]	Gabor & SVM	Based on Linear Classifier Not effective for Non-Linear Data	97.12 %
Vijay E V et al. [5]	Modified-SVM	Based on Modified Linear Classifier Not effective for Non-Linear Data	96.77 %
R. Pittman, B. Hu et al. [6]	LIDAR	Based on Light Detection Less effective for texture analysis	79.50 %
M van Rooyen, N Luwes [13]	SVM	Implementing custom software to implement a complete machine vision solution is unnecessary and can take month to complete.	-
Srunitha. k et al. [14]	HSV-SVM	Based on HSV color model Recognition using color is not effective for better precision before classification	95.00 %
Shravani V1, Uday Kiran S2 [15]	Naïve Bayes	System uses Naive Bayes classifier for classifying soil but Naive Bayes is suitable to linear data but not suitable for non linear data.	92.93 %

III. PROPOSED IMPLEMENTATION

The point of the framework is to distinguish the soil type alongside its elements. The proposed work can naturally order the soil type by utilizing Histogram Equalization Transform and Support Vector Machine. Polynomial Support Vector Machine is the best classifier for classifying the soil with a superior degree of precision. The framework pre-handled the information by certain preprocessing approaches before classification. The framework has been carried out by utilizing a polynomial Support Vector Machine that improves the precision as well as the processing time. For the execution of the framework, the MATLAB structure has been utilized alongside ODBC and MySQL data set for putting away the dataset results for each test. Pre-processing means to further develop image data that abatements and additions unfortunate curves a few images are significant for the front image readiness. The objective of image improvement is to manage an image to construct the detectable quality of the part of interest. Division is the pattern of eliminating an area of interest from a given image. Area of interest containing each pixel comparative characteristics. Here we are using most extreme entropy thresholding for division. Support vector for straight forwardness machine classifiers is used here. Takes set of SVM predicts images and for every data image which of the two classes of infection and non-harmful development. SVM intends to make hyper plane that segregates the two squares most extreme differentiation between them.

A. Histogram Equalization

Histogram equalization is the process of adjusting the brightness and contrast of an image and enhances the visibility of foreground object. By the help of histogram equalization the background can be segmented effectively by thresholding method. In the given example, the x-axis addresses the gray apparent scale (where dark on the left side and white on the right one), and the y-axis addresses the quantity of pixels in an image. Here, the histogram addresses the quantity of pixels for brightness level at each point, and when there is more pixel power with steady color, and then the pinnacle will be higher for each fixed brightness level.

$$P_n = \frac{number\ of\ Pixel\ Intensity\ n}{Total\ number\ of\ pixels}\ n = 0,1 \ldots .L-1$$

Where Pn is the affected pixel value after histogram equalization. The histogram equalized image γ will be defined as:

$$\gamma_{i,j} = floor\left((L-1)\sum_{n=0}^{f_{i,j}} P_n\right),$$

Where floor() can be considered as the nearest integer. It is equivalent to pixel intensity k;

$$k = floor\left((L-1)\sum_{n=0}^{f_{i,j}} P_n\right)$$

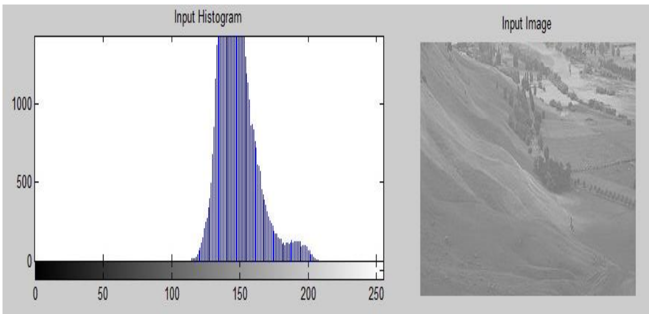


Fig. 4. Before Histogram Equalization

Histogram equalization is an advanced image handling technique which has been utilized for further developing contrast or changing it in images. It achieves by effectively spreading the most noteworthy force values. This technique ordinarily builds the worldwide contrast of images. It permits a higher contrast to be accomplished for districts of low nearby contrast.

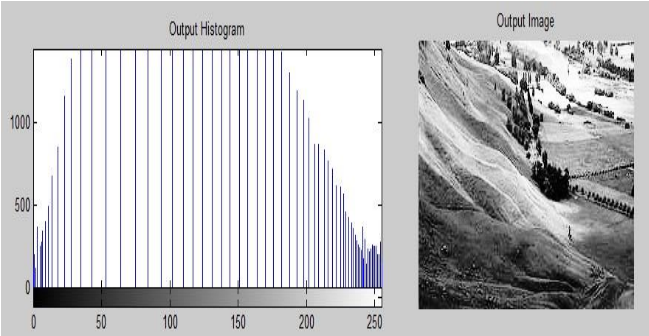


Fig. 5. After Histogram Equalization

Fig. 6. Histogram Equalization of Soil Textures

B. Polynomial Support Vector Machine

Support Vector Machine is method of classifying data on the basis of their patterns or appearance. SVM is considered as the most robust prediction technique that can classify data with more preciseness. Here system uses non linear SVM to deal with the non linear data. Most of the medical data belongs to the non-linear classes because of complex structure of blood vessels. Fig 1.10 shows the separation of data with hyperplane.

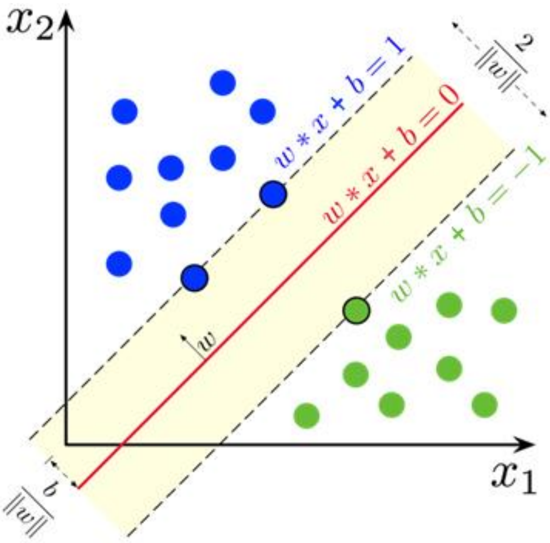


Fig. 7. Support Vector Machine for Two Sample Classes

Every hyperplane can be written as;

$$w * x + b = 1$$
$$w * x + b = 0$$
$$w * x + b = -1$$

Where w is the normal vector, b is the bias, x is the data points. If data point is on the hyperplane then it would be; $w * x + b = 0$ otherwise it would be either negative or positive. It is required to know that which data points are closer or nearer to the hyperplane.

$$h(x_i) = \begin{cases} +1 \; if \; w.x + b \geq 0 \\ -1 \; if \; w.x + b < 0 \end{cases}$$

It is required to maintain the balance of the classification between maximization and loss. It can be stated as;

$$min_w \; \|w\|^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)$$

C. Flow Chart

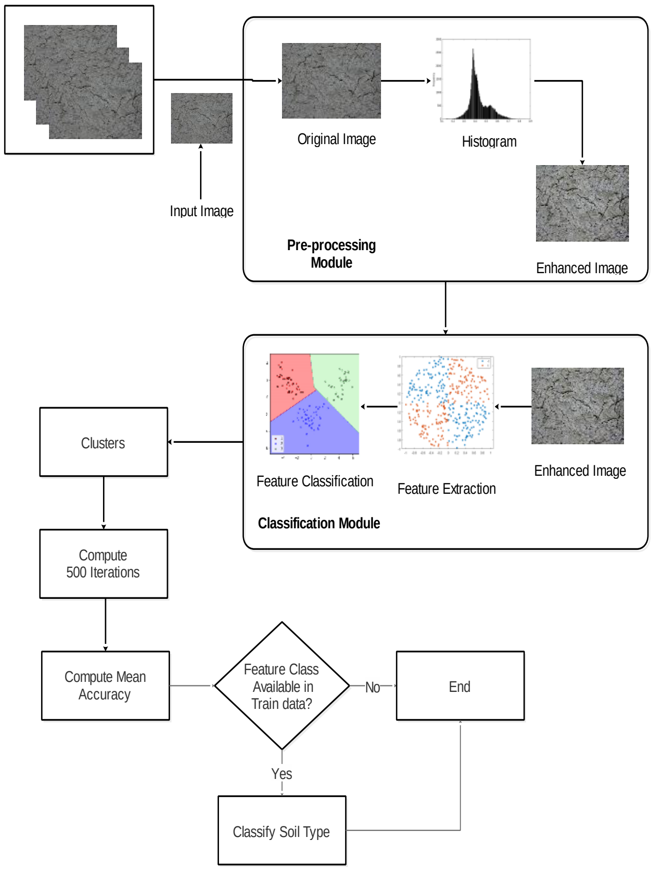


Fig. 8. Flow Chart of the Proposed System

First of all; a soil image has been selected to test the system and once the image has been selected, the pre-processing module has been initiated and image is about to enhanced in its texture. The enhanced image is liable to become more visible as compare the input one. Histogram equalization is a process that can enhance the image's visibility at its possible extents. One the image has been enhanced then classification module has been initiated. Features have been extracted from the enhanced image matrix and then SVM makes the clusters for similar kind of particles. Once the clustering processing has been done then system is able to classify the clusters using hyperplane. Then a distinct cluster has been pertained and through which accuracy can be achieved using 500 iterations. Then Mean accuracy can be calculated of 500 iterations. Then system matches the texture with the train data and if data features are available then system classifies the soil type and system end the process out there.

D. Algorithm

Polynomial SVM Algorithm

Initialization

Input: Set of Image I=(i_1, i_2, i_3 ,……… i_n)

Output: Classification

Step 1: Input image

Step 2: Apply histogram equalization

$$P_n = \frac{number\ of\ Pixel\ Intensity\ n}{Total\ number\ of\ pixels} \quad n = 0,1 \ldots .L-1$$

Where Pn is the affected pixel value after histogram equalization.

Step 3: Collect data points from histogram affected matrix as vectors w_i.

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 \ldots \ldots \ldots$$

$$= w_0 + \sum_{i=1}^{m} w_i x_i$$

$$w_i = w_0, w_1, w_2 \ldots \ldots \ldots \ldots . w_m$$

Where w_i is the vector, b is the bias and x is the variable

Step 4: Calculate the margin

$$w * x + b = 1$$

$$w * x + b = 0$$

$$w * x + b = -1$$

$$h(x_i) = \begin{cases} +1 \ if \ w.x + b \geq 0 \\ -1 \ if \ w.x + b < 0 \end{cases}$$

Step 5: Compute loss function

$$min_w \ \|w\|^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)$$

Step 6: do {

Compute iterations;

} While (I_t < 500);

Step 7: Compute mean accuracy

$$\bar{X} = \sum_{i=1}^{500} \frac{X}{N}$$

Where $\bar{X}$ is the mean accuracy of the system, X is the individual accuracy from iterations, N is the total number of iterations.

Step 8: if F ∈ T then

Classify Soil Type;

else

No Classification;

end else

end if

Step 9: End

IV. Result

The system has been tested with 175 soil images of different categories that belong to Clayey Sand, Clayey Peat, Humus Clay and Silty Sand, Sandy Clay. System recorded 97.78 % as mean accuracy of the system which is bit higher than the earlier one i.e. 97.57 %. Soil features are based on various key factors such as Color Moments, HSV Histogram, Mean Amplitude, Auto Correlogram, Wavelet Moments and Energy. There are 175 tests are done where 11 images for each categories. Each image has its own 500 iterations along with various features points such as Color Moments, HSV Histogram, Mean Amplitude, Auto Correlogram, Wavelet Moments and Energy.

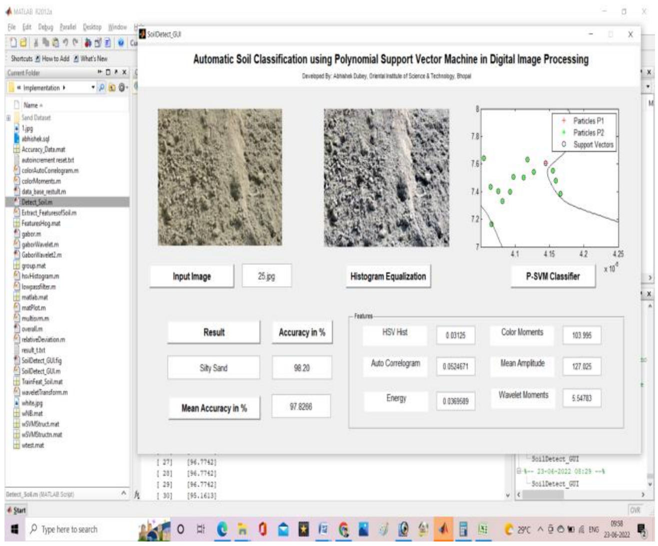


Fig. 9. Proposed System

Table No. I Experimental Results

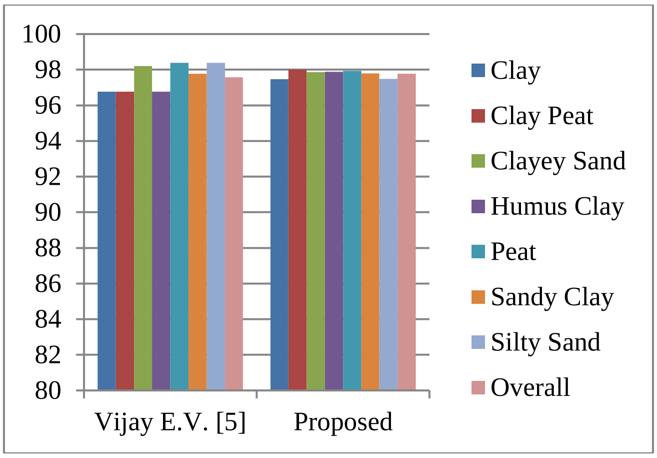
Soil Type	Proposed in %
Clay	97.47
Clay Peat	98.00
Clayey Sand	97.86
Humus Clay	97.88
Peat	97.94
Sandy Clay	97.8
Silty Sand	97.48
Overall Accuracy	97.78

Table I shows the experimental result of the proposed system for clay, clay peat, clayey sand, humus clay, peat, sandy clay and silty sand. System pertain 97.78 % of overall mean accuracy.

Table No. II Result Comparison

Soil Type	Vijay E.V. [5]	**Proposed**
Clay	96.77	**97.47**
Clay Peat	96.77	**98.00**
Clayey Sand	**98.20**	97.86
Humus Clay	96.77	**97.88**
Peat	**98.38**	97.94
Sandy Clay	97.77	**97.80**
Silty Sand	**98.38**	97.48
Overall Accuracy	97.57	**97.78**

Graph No. I Result Comparison



V. Conclusion

The automatic soil classification using Polynomial Support Vector Machine is a novel approach for classifying the soil type along with various features such as Color Moments, HSV Histogram, Mean Amplitude, Auto Correlogram, Wavelet Moments and Energy. P-SVM is able to deal with non-linear data and soil has complex in structure and it's hard to predict the soil type. System pertained 97.78 % of overall mean accuracy for all seven types of soil which is bit higher than the previous system. In future accuracy can be enhanced with minimal false acceptance rate by using better modern classifier than SVM or by using deep learning model by minimizing the weight of the model with smart filters and better utilization of layers.

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