IJARST

International Journal of Advanced Research in Science and Technology

https://doi.org/10.62226/ijarst20241388

ISSN 2319 – 1783 (Print)

ISSN 2320 – 1126 (Online)

Performance Analysis of Vector Machine Learning Algorithm based Plant Leaf Disease Detection and Soil Type Classification

Jaya Bharti Sharma*[1] and Prof. Satnam Singh Dub[2]

[1,2]Sri Sai College of Engineering & Technology, Badhani, Pathankot, Punjab India

jayabhartil31@gmail.com[1]*

ARTICLEINFO

Article history:

Received	13 May 2024
Accepted	24 May 2024
Available online	10 June 2024

Keywords:
VECTOR MACHINE LEARNING,
L-NL CLASSIFICATION,
DIP,
MATLAB.

ABSTRACT

The objective is to create and evaluate an image processing application designed for identifying leaf diseases and classifying soil types, utilizing a combination of Linear-Non-Linear (L-NL) Classification Techniques and the Vector Machine Learning (VML) Algorithm. We go over the methods created and put to the test for automating the process of classifying soil types and leaf diseases. The majority of methods begin by segmenting the measured signals from the acquired data using a segmentation algorithm. Next, effective extraction techniques are employed to extract the valuable information from these segments. Certain classifiers that are specifically designed to assign classes to these segments are constructed using the measured data and features that were extracted from the collected samples; these classifiers may make use of VML methods. Cone penetration testing collected data was utilised in the traditional approach for categorising subsurface soil, and positive outcomes were attained. In the past, classification systems required a domain expert to observe the trends and size of the segmented signals in addition to any accessible a priori knowledge. The suggested methods for employing image processing to automate this classification process are also included in this paper. Boundary energy approach can be used to extract the prominent aspects of the observed segments from a segmentation algorithm, for example. Dedicated linear and non-linear classifiers assign classes to the observed segments based on the measured data and attributes taken from the gathered data of soil and damaged and healthy plant leaves. Then, VML algorithm classification is applied. In summary, the procedure begins with the application of feature extraction methods in image processing to identify the characteristics of soil samples and leaf images. Subsequently, a database of these sample images is created. The classification of soil types and leaf diseases is then performed based on their vector features using the VML algorithm.

Introduction:

India is the land of agriculture. Farmers have an option to select required crops and then find appropriate pesticides for the plant to decrease the disease and increase the production. The cultivated plants will not always be healthy. In-order to increase the production with good quality the plant needs to be monitored frequently because the plant disease leads to reduction of the product. For successful cultivation, one should monitor the health as well as the disease of the plant. Diseases in plant cause heavy loss of the product. India is the world's highest producer of pomegranate. India exports tons of agricultural products. Hence the disease needs to be identified at the early stages, recommending farmers to avoid the harm in production of the crop to increase the yield [1].

Soil is a crucial resource and a vital component of Earth's critical zone, providing essential ecosystem services such as water filtration and nutrient supply to vegetation, which in turn supports food, energy, and fiber production, crucial for human health and habitation. However, urbanization, industrialization, and degradation are exerting extraordinary pressures on soil, diminishing its quality and disrupting agricultural practices and food production. Therefore, managing soil quality and planning for its preservation is essential to ensure its sustainability for future generations. Soil mapping and classification are integral to landform management and sustainable land use planning. Digital assessment and classification of soil properties, along with mapping, are critical for agricultural practices like crop growth and condition monitoring, as global food production largely depends on soil nutrients.

Nonetheless, soils are highly heterogeneous and dynamic compared to air and water, making their structure, study, and processes complex both spatially and temporally. Soil is a key factor in environmental changes, such as deforestation, habitat fragmentation, urbanization, and wetland degradation. While soil pertains to the physical features or vegetation on the land, land use concerns the economic activities or purposes to which the land is devoted. Consequently, soil classification has become a significant area of research in engineering. Engineers require fundamental information about the type and structure of the soil. VML Algorithms are based on the concept of decision planes that define decision boundaries. VML Algorithms are a group of supervised learning methods utilized for classifying diverse objects. In supervised learning, the algorithm analyzes a given training set to predict labels for the test set. These algorithms construct hyperplanes in an infinite-dimensional space, which are then employed for classification purposes or other experiments. A hyperplane achieving the largest distance to the nearest training data point of any class, known as the margin, facilitates better separation. Minimizing the functional margin helps to reduce the generalization error of the classifier. The widespread acceptance of computers across various engineering fields is evident, with geotechnical engineering making significant strides in this regard. Utilizing computers automates the characterization process of soil types and plant leaf diseases, enhancing objectivity and reducing the likelihood of human error. This automation saves significant amounts of energy, time, and money. This research focuses on measuring and employing various image-based parameters for the classification of plant leaf diseases and soil types [2].

Literature Review:

Kusumo *et al.* explore various image processing features for the detection of corn diseases. These features include RGB color detection, local features such as Scale-Invariant Feature Transform, Speeded Up Robust Features, and Oriented FAST and Rotated BRIEF, as well as object detection methods like Histogram of Oriented Gradients. They assess the performance of these features across multiple machine learning algorithms. Implementing machine learning techniques can mitigate the risks associated with crop failure caused by disease outbreaks. Traditional inspection methods rely on visual cues such as changes in color or the presence of spots or areas of decay on the leaves [3].

Pardede *et al.* present an unsupervised feature learning algorithm using the convolutional AutoEncoder for detection of plant diseases. The use of convolutional AutoEncoder has two main advantages. First, the use of handcrafted features is not necessary as the network itself may learn to produce discriminative features. Secondly, the procedure is conducted in an unsupervised manner and hence, no labeling of the data is required. Here, we use the output of the Auto Encoder as inputs to SVM-based classifiers for automatic detection of plant diseases [4].

Bhimte et al. present a system using simple image processing approach for automatic diagnosis of cotton leaf diseases. Classification based on selecting appropriate features such as color, texture of images done by using SVM classifier. The images are acquired from cotton fields using a digital camera. Various preprocessing techniques as filtering, background removal and enhancement are done. Color-based segmentation is done to obtain the diseased segmented part from the cotton leaf. Segmented image is used for feature extraction [5].

Chopda et al. propose a system which can predict cotton crop diseases using 'Decision Tree Classifier' by taking parameters as temperature, soil moisture, etc. This would help farmers by providing better quality productions and they would be also focusing on building an android application which will give real time output to the farmers in efficient ways [6].

Aparna et al. introduce algorithms for detection of weeds, pest and disease affected leaves in a maize field. Shape and size analysis techniques are used for weed detection while thresholding methods are used for pest and disease affected leaves detection. The algorithms can be used in systems to enable automated precision agriculture in maize fields. Managing the agricultural sector by exploiting technology facilitates the productivity as well as diminishes unintended wastages and manual inaccuracies [7].

Kumar et al. concentrate on designing and developing an embedded system framework to evaluate the suitability of soil for urban terrace farming. With this system, the necessity to frequently consult an agricultural officer or department for soil quality and type testing can be significantly reduced. It assists users in selecting the most suitable plants (especially cash crops) and fertilizers for the existing soil conditions. The system estimates soil conditions by measuring pH and moisture content, utilizing hydrogen ion concentration and moisture sensors to determine the appropriate levels for specific cash crops [8].

Kumar et al. suggest that flexible pavement structures consist of multiple layers, each designed with different materials to minimize stress on the subgrade. In recent decades, the incorporation of industrial products in pavement construction has garnered significant attention. This paper aims to determine the optimal percentage of glass powder to use as a soil stabilizer for enhancing the performance of the base layer. Additionally, it identifies a suitable machine learning technique to predict soil strength. The study employs two machine learning methods: SVM and Artificial Neural Network (ANN). Various performance metrics such as RMSE, R-Squared, MSE, MAPE, MAE, and Chi-square are calculated and compared between ANN and SVM. [9].

Biswas et al. apply various models including General Regression Neural Network (GRNN), ANN, Fully Connected Neural Network (FCNN), Support Vector Regression (SVR), and Linear Regression (LR) to predict soil composition concerning Standard

Penetration Test (SPT) values and soil depth. The main emphasis lies in establishing a substantial correlation between soil composition, SPT values, and depth [10].

C. Dewi et al. assert that optimal growth of essential oils plantation necessitates adequate nutrients and organic matter. This research introduces a novel approach for determining soil organic matter content by leveraging soil images and distance-based classification algorithms such as KNN and Weighted KNN. However, a challenge with distance-based algorithms lies in the calculation techniques, which can yield significant disparities. Thus, the study evaluates the effectiveness of various distance formulations—Manhattan, Euclidean, and Minkowsky. Features utilized as input for the recognition process are extracted using the GLCM method [11].

Methodology:

Leaf Disease Detection: Process

In the current system, a range of image processing techniques including Probabilistic Neural Network, Genetic Algorithm, and Support Vector Machine are employed. However, the outcome quality may fluctuate based on the input data, demanding extensive effort, expertise in plant diseases, and substantial processing time.

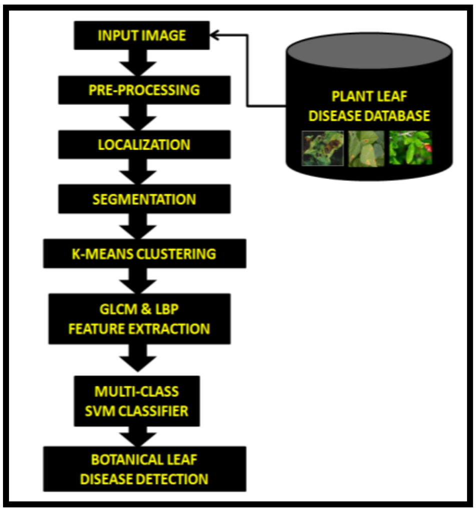

Fig 1_Leaf Disease Detection Process

Leaf Disease Detection: Process Flow Algorithm

Step 1: Image Input/Acquisition: This stage entails capturing high-quality images of both healthy and diseased leaves with excellent clarity, ensuring good brightness and contrast. The initial phase begins by acquiring a collection of leaf images.

Step 2: Image Pre-processing: Image preprocessing is conducted at the lower level to address any distortions and noise present in the images, thereby enhancing them for subsequent processing.

Step3: Apply K-means clustering Segmentation: For segmentation, the K-means clustering method is employed to partition the images into clusters, ensuring that at least one cluster contains the major area of the diseased part. This algorithm categorizes objects into K classes based on a defined set of features, aiming to minimize the sum of squared distances between data objects and their respective clusters.

Step 4: Gray Level Co-occurrence Matrix (GLCM) & LBP Features

Feature extraction is a technique used to efficiently describe a large dataset accurately, requiring various resources. Statistical texture features are derived using the GLCM formula for texture analysis. These features are computed from the statistical distribution of observed intensity combinations relative to others at specified positions. The number of gray levels is crucial in GLCM, and statistics are classified into first, second, and higher orders based on the intensity points in each combination. Several statistical texture features of GLCM include energy, sum entropy, covariance, information measure of correlation, entropy, contrast, inverse difference, and difference entropy.

Pattern in Local Binary: The local binary partition measure is a straightforward yet effective method for analyzing texture. It involves examining the intensity of eight neighboring pixels surrounding each pixel in the image. These intensities are used to create an eight-digit binary number, with "0" representing cases where the neighbor's intensity is less than or equal to that of the central pixel, and "1" otherwise. By constructing a histogram of these binary numbers, the image is effectively represented.

Step 5: Disease Classification: A binary classifier that utilizes a hyperplane, referred to as the decision boundary, to distinguish between two classes is known as VML.VML is based on the concept of decision planes that define decision boundaries which consists of set of related supervised learning method used for classification of various objects. Supervising learning technique involves analyzing of given training set and predicts labels of the test set.

System Design: Soil Testing

The proposed system for classifying soil samples based on images consists of five primary steps: image acquisition, image enhancement, feature extraction, classifier training, and image-based soil sample classification.

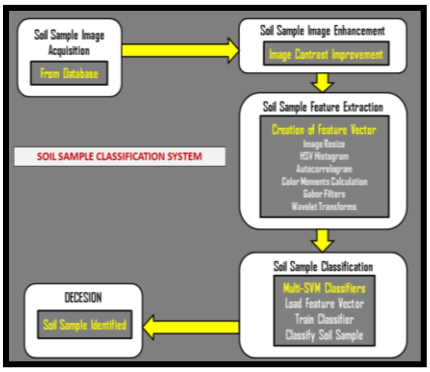

Fig 2_Proposed Soil Sample Classification System

The proposed study focuses on utilizing image processing techniques to detect soil samples. The method comprises two key components. The first part involves database formation, which is crucial during the training phase. The second part entails actual classification during the testing phase.

Training: During the training phase, the initial step involves gathering various pictures of soil samples. Subsequently, preprocessing techniques are applied to these soil images. An algorithm is then formulated to extract features from the soil sample images, utilizing methods such as HSV Histogram, Color moments (Mean Standard Deviation), Gabor features, and Color Auto correlogram. Following feature extraction, a database is constructed, comprising prepared features from the sample images. Lastly, an SVM algorithm is developed to determine the class.

Testing: Choose any image of a soil sample for testing purposes. which will go through procedures like feature preparation, feature extraction, and preprocessing. Create a VML algorithm to identify the soil class. MATLAB may be used in the algorithm's implementation.

Picture of soil: Various soil types exist, including Peat, Sandy soil, and clay, among others.

Prior to processing: This section contains methods that have been enhanced and will aid in the feature extraction process.

Enhancement: Image enhancement involves modifying digital images to make them more suitable for display or subsequent image analysis. This process can include tasks such as noise reduction, sharpening, or adjusting brightness, all aimed at improving the identification of essential features within the image.

Feature Extraction: In this stage, methods such as HSV Histogram, Color moments (mean Relative Deviation), Gabor features, and Color Auto correlogram are employed to extract soil features.

Feature Data Preparation: The extracted features are computed and documented.

Feature Database: The calculated feature values are grouped to form a feature database, which is then inputted into the SVM Classifier for soil type classification.

Vector Machine Learning Classification: VML comprises supervised models that utilize learning algorithms to analyze data for regression and classification purposes. When presented with a set of training examples categorized into two groups, a support vector machine algorithm trains a model to classify new instances into one of these categories using a non-probabilistic binary classifier.

Results and Discussions:

Performance Analysis of Leaf Disease Detection

The Leaf Disease Detection application is tested on five different datasets of Botanical Leaf Disease database with a total of 75 leaf images**.** The first four datasets consist of different number of leaf images which affected be a specific leaf disease and the last dataset comprises of healthy leaf images.

The first dataset referred to as **Leaf Disease Dataset 1 (LDD1)** consists of a total of 22 leaf images which belong to a particular set of plant leaf disease called **Alternaria Alternata** which is a fungus which has been recorded causing leaf spot and other diseases on over 380 host species of plant. It is an opportunistic pathogen on numerous hosts causing leaf spots, rots and blights on many plant parts.

The second dataset referred to as **Leaf Disease Dataset 2 (LDD2)** consists of a total of 23 leaf images which belong to a particular set of plant leaf disease called **Anthracnose** which is a also fungal disease that affects many plants, including vegetables, fruits, and trees. It causes dark, sunken lesions on leaves, stems, flowers, and fruits. It also attacks developing shoots and expanding leaves. .

The third dataset referred to as **Leaf Disease Dataset 3 (LDD3)** consists of a total of 06 leaf images which belong to a particular set of plant leaf disease called **Bacterial Blight** (*Pseudomonas savastanoi*) which is as name suggests a bacterial infection, typically an early season disease, which over winters in the field on plant residue. Initial infection occurs when wind or splashing water droplets from plant residue on the soil surface to the leaves carry bacterial cells.

The fourth dataset referred to as **Leaf Disease Dataset 4 (LDD4)** consists of a total of 09 leaf images which belong to a particular set of plant leaf disease called **Cercospora Leaf Spot** a fungal infection which can be caused by many different Cercospora fungal pathogen species depending on the plant type infected.

The fifth and final dataset referred to as **Leaf Disease Dataset 5 (LDD5)** consists of a total of 15 leaf images which belongs to healthy plant leaf images with no indication of disease formation of any sorts on the leaf.

Application Testing and Result Analysis (Plant Disease Detection)

The testing procedure includes the testing of each Dataset of leaf disease images on the application GUI for Botanical Leaf Disease Detection/Classification System developed using MATALB GUIDE and recording and data logging of calculated feature and result parameters for further performance analysis. A total of 16 parameters are recorded after testing every image for each dataset. The three parameters namely Match, %Region affected and %Accuracy correspond to the performance of VML Classifiers for Disease Classification and the rest correspond to k-means clustering Segmentation and Feature Clustering using GLCM and LBP.

Match: For every correct disease classification or detection from each dataset the exact Match is assigned a high value i.e. 1 and for incorrect or no match it is assigned a low value i.e. 0.

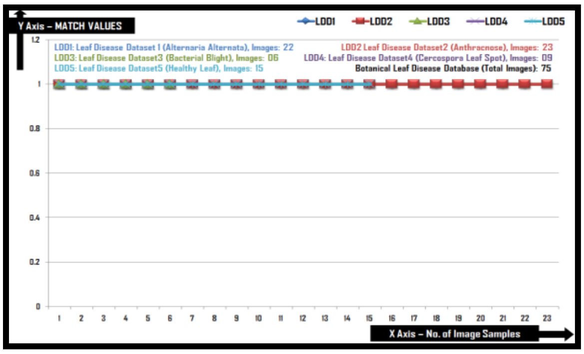

Fig 3_Graph: Match Results for each Dataset

% Region Affected: This parameter gives the quantitative analysis of the spread of disease on the leaf and corresponds to the amount of region on the query leaf image on which the disease in spread and is calculated and denoted in percentage.

% Accuracy: This parameter gives the qualitative analysis of the spread of disease on the leaf and corresponds to the efficiency with which the multiclass SVM classifier function classifies the disease in question in the query image gives the exact match over a period of 500 iterations on the query leaf image and thus the accuracy is calculated and denoted in percentage.

Mean: The mean indicates the average gray level value within the image. Higher mean values typically correspond to images with higher overall gray level sums.

Mean = (values of the pixels in the image) / (Number of pixels in the image).

Standard Deviation (SD): SD measures the extent of variation or dispersion within a dataset. A low standard deviation suggests that the data values are closely clustered around the mean, while a high standard deviation indicates that the data is spread out over a wider range of values.

Skewness measurements: Skewness is a measure of a distribution's symmetry or lack thereof. It quantifies how much a distribution deviates from being perfectly symmetrical around its center point. Typically calculated as the normalized third moment, skewness indicates whether the distribution is skewed left or right. A skewness value of zero suggests symmetry, with negative values indicating left skewness (a longer left tail) and positive values indicating right skewness (a longer right tail). For instance, a Normal distribution has a skewness of zero, while any symmetric dataset should have skewness near zero.

Mathematically,

If skewness>0 Then distribution is right skewed. That means mean>median.

Most values are concentrated on left of the mean, with extreme values of the right.

If Skewness<0 Then distribution is left skewed. That means mean<median.

Most values are concentrated on the right of the mean with extreme values of the left.

If Skewness=0 it means Mean=median

The distribution is symmetrical around the mean.

Measures of Kurtosis: Right skewness indicates that the right tail of the distribution is longer compared to the left tail, often observed in measurements with a lower bound. Kurtosis measures the peakedness or flatness of data relative to a normal distribution. High kurtosis suggests a pronounced peak near the mean, rapid decline, and heavy tails, while low kurtosis indicates a flatter distribution with a less distinct peak. Histograms are useful visual tools for illustrating both the skewness and kurtosis of datasets.

Gray Level Histogram Based Features: In the histogram-based approach, texture analysis relies on the intensity values of either the entire image or a specific region within it. These intensity values offer statistical insights, which can be examined using various statistical methods to assess the gray values. Features extracted from the gray level histogram approach encompass diverse moments, which are outlined below.

Quantity of pixels: The classification can be divided into first-order, focusing on individual pixels and estimating their properties, and higher-order, which involves properties of two or more pixel values. Statistical techniques such as mean, standard deviation, variance, and skewness are commonly applied. The co-occurrence matrix emerges as an effective method, offering pixel values at various relative locations.

Moment (IDM): Classification based on the first moment (mean), second moment, third central moment, and fourth central moment.

Co-Occurrence Matrix: A co-occurrence matrix, represented by a two-dimensional array C, encompasses a range of possible image values V within both its rows and columns. While co-occurrence matrices effectively capture texture properties, they are not inherently suitable for direct comparison between textures. Instead, numerical features are derived from the co-occurrence matrix to provide a more concise representation of the texture.

The following are the Standard co-occurrence matrix.

Energy: Energy serves as a gauge for localized changes within an image. Although it may go by various names across different contexts, it generally signifies the rate of alteration in pixel color, brightness, or magnitude over small regions. This phenomenon is particularly evident along the edges or boundaries within an image, where compression tends to be most challenging due to rapid gradients. Despite the varying terminologies, they all point to this fundamental concept. '**Energy**' is a minimization problem or maximization one, it depends on your goal. It is used in typical object detection or **segmentation** tasks where it is posed as an **Energy** minimization problem.

Entropy: In images, Entropy represents the variety of intensity levels that individual pixels can exhibit. It serves as a quantitative measure for analyzing and assessing image details, with its value offering a more effective means of comparing these details.

Contrast: Image enhancement techniques are extensively employed in various image processing applications, especially when the subjective quality of images is crucial for human interpretation. Contrast plays a vital role in assessing image quality subjectively, as it arises from variations in luminance between adjacent surfaces. Essentially, contrast enables the distinction of objects from both other objects and the background. In visual perception, contrast is predominantly influenced by differences in color and brightness among objects. Interestingly, our visual system is more attuned to contrast rather than absolute luminance, enabling consistent perception of the world despite varying illumination conditions. Consequently, numerous algorithms have been developed for enhancing contrast, addressing diverse challenges in image processing.

Correlation: **Correlation** computes a measure of similarity of two input **images** as they are shifted by one another. The **correlation** result reaches a maximum at the time when the two **signals** match best.

Homogeneity: It signifies the level of smoothness within an image. The segmentation of images is achieved automatically through the utilization of measures such as 'homogeneity' and 'contrast,' which are defined based on the co-occurrence matrix of the image. The contrast measure incorporates the concept of logarithmic response within an image system. Additionally, a merging algorithm is introduced to eliminate undesirable thresholds. The effectiveness of this algorithm is demonstrated, along with a comparison of its performance against existing methods, using a set of images.

Application Testing Procedure for Soil Testing

The results are obtained for Vector Learning Algorithm Soil Type Classification and Analysis System by development of a robust user-interface in MATLAB using GUIDE. The application GUI for Soil Type Classification and Analysis System using Multi-Class VML Algorithm is developed and tested using database entry samples for Soil Classification Database of subsets of 07 different soil types mages. The Soil Classification Database consists of total of 175 soil images with 25 images of 07 different individual soil types.

Soil Classification Dataset	Soil Type	Image Samples	Match	No Match	% Accuracy	% Error
SCD1	Clay	25	25	0	100	0
SCD2	Clayey Peat	25	24	1	96	4
SCD3	Clayey Sand	25	25	0	100	0
SCD4	Humus Clay	25	24	1	96	4
SCD5	Peat	25	25	0	100	0
SCD6	Sandy Clay	25	24	1	96	4
SCD7	Silty Sand	25	25	0	100	0
Total Input Images						175
Total Accurate Classifications						172
Total Inaccurate Classifications						03
Overall System %Accuracy						98.3
Overall System %Error						1.8

Fig 4_Soil Type Dataset Details

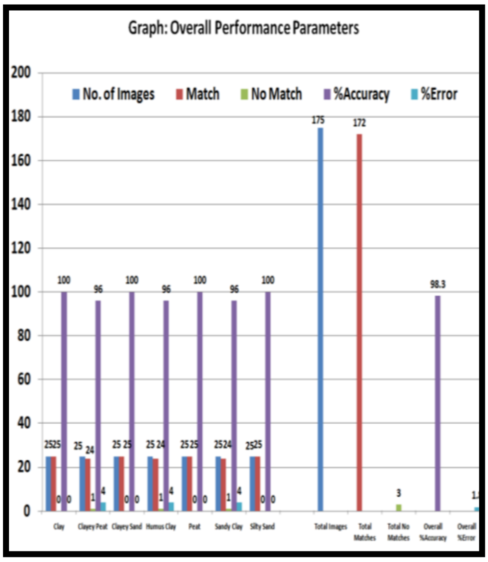

Fig 5_ Soil Type Classification: Overall Performance Parameters

Conclusion:

The primary objective of the Plant Disease Detection Application is to create an image processing system capable of identifying and categorizing four types of plant diseases. Through the utilization of a VML classifier, experimentation is conducted on a dataset comprising 75 images. The accuracy of the classification varies across different images. In disease detection, the disease affected portion of the plant leaf is first identified using GLCM and LBP features and then VML classifier. The detection accuracy rate is 100%. So, GLCM and LBP features and then VML classifier obtained the high accuracy rate for classification of plant diseases. Also, transformation features were used to classify the soil images using VML Classifier. The features utilized include HSV Histogram, Color Moments, Auto-Correlation, Wavelet Moments Mean, and Energy. Employing a VML classifier, experimentation is conducted on a dataset comprising 175 images. The accuracy rate stands at 100% for four soil types and 96% for three soil types. The overall system accuracy for the 175 images is computed at 98.3%, with a minimal error rate of 0.02% and an error percentage of 1.8%.

References:

1. M. H. Ahmed, T. Islam and R. R. Ema, "A New Hybrid Intelligent GAACO Algorithm for Automatic Image Segmentation and Plant Leaf or Fruit Diseases Identification Using TSVM Classifier," 2019 IEEE International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox's Bazar, Bangladesh, 2019, pp. 1-6. doi: 10.1109/ECACE.2019.8679219

2. G. Kaur, K. Das and J. Hazra, "Soil Nutrients Prediction Using Remote Sensing Data in Western India: An Evaluation of Machine Learning Models," *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, 2020, pp. 4677-4680, doi: 10.1109/IGARSS39084.2020.9324201.

3. B. S. Kusumo, A. Heryana, O. Mahendra and H. F. Pardede, "Machine Learning-based for Automatic

Detection of Corn-Plant Diseases Using Image Processing," 2018 IEEE International Conference on Computer, Control, Informatics and its Applications (IC3INA), Tangerang, Indonesia, 2018, pp. 93-97. doi: 10.1109/IC3INA.2018.8629507

4. H. F. Pardede, E. Suryawati, R. Sustika and V. Zilvan, "Unsupervised Convolutional AutoEncoder-Based Feature Learning for Automatic Detection of Plant Diseases," 2018 IEEE International Conference on Computer, Control, Informatics and its Applications (IC3INA), Tangerang, Indonesia, 2018, pp. 158-162. doi: 10.1109/IC3INA.2018.8629518

5. N. R. Bhimte and V. R. Thool, "Diseases Detection of Cotton Leaf Spot Using Image Processing and SVM Classifier," 2018 IEEE Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2018, pp. 340-344. doi: 10.1109/ICCONS.2018.866290

6. J. Chopda, H. Raveshiya, S. Nakum and V. Nakrani, "Cotton Crop Disease Detection using Decision Tree Classifier," 2018 IEEE International Conference on Smart City and Emerging Technology (ICSCET), Mumbai, 2018, pp. 1-5. doi: 10.1109/ICSCET.2018.8537336

7. K. Aparna and P. Supriya, "Precision Agriculture in Maize Fields," 2018 IEEE Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2018, pp. 1407-1410. doi: 10.1109/ICCONS.2018.8662936

8. P. M. Kumar, T. Ganesh Sai Kumar, R. Aravindhan, D. Sairam and S. Moorthi, "Design and Development of an Embedded Framework to test Soil for Urban Terrace Farming," *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)*, 2020, pp. 41-45, doi:10.1109/ICETCE48199.2020.9091731.

9. D. D. Kumar and D. Harinder, "ANN and SVM Based modeling of stabilized soils," *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 2020, pp. 748-755, doi: 10.1109/I-SMAC49090.2020.9243557.

10. Suparna Biswas, Tarek Ibne Faysal, Arshi Siddiqui Promiti, Md. Sazzad Hossain, Lubaba Bazlul and Abdullah Md. Sarwar, "Analysis of Soil and Various Geo-technical Properties using Data Mining Techniques," *2020 IEEE 10th International Conference on Intelligent Systems (IS)*, 2020, pp. 288-293, doi: 10.1109/IS48319.2020.9199941.

11. C. Dewi and Y. K. Arbawa, "Performance Evaluation of Distance Function in KNN and WKNN for Classification of Soil Organic Matter," *2019 International Conference on Sustainable Information Engineering and Technology (SIET)*, 2019, pp. 196-199, doi: 10.1109/SIET48054.2019.8986030.