Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 6, pp. 4518–4528, DOI 10.12694/scpe.v25i6.3258

IDENTIFYING CROP DISTRESS AND STRESS-INDUCED PLANT DISEASES USING HYPER SPECTRAL IMAGE ANALYSIS

BYUNGCHAN MIN*

Abstract. The purpose of this study is to determine whether hyper spectral images can be used to identify plant diseases and crop pressure from aerial photographs. With extensive research on the prevalent methods used closer to the problem, this study offers a potent strategy for identifying crop distress and illnesses using this efficient imaging technique. To identify the spectral fingerprints of common indications and symptoms of plant diseases and crop strains, this study evaluates the available hyper spectral photo datasets. After that, the data are examined using two learning algorithms—the highly randomized trees and the Random Woodland set of rules—to create predictions that are entirely dependent on the results that are discovered. In the end, a benchmarked set of test statistics is used to assess the prediction accuracy. The results of this study show that hyper spectral photo evaluation has a strong and promising utility for crop stress and disease identification. Hyper spectral light evaluation is a method for identifying plant diseases caused by strain on crops. By gathering and evaluating high-dimensional spectral reflection data from satellite or aircraft structures, details regarding the physiological homes of flowers can be identified. The health of plants, illnesses brought on by stress, and agricultural productivity predictions can all be made using these facts. Hyper spectral recordings can also be used to create actions that reduce agricultural losses and enhance the health of plants that are prone to disease.

Key words: Hyper Spectral Images, Crop Pressure, Plant Disease, Accuracy, Crop Pressure.

1. Introduction.

To develop effective management measures to provide wholesome and nutritious meals, it is essential to be able to identify plant diseases caused by stress and crop distress [1]. A useful tool for accurately identifying differences in agricultural fields, identifying capacity problems, and implementing manual interventions to reduce illness and suffering is hyper spectral picture analysis. In classical distant sensing, detection is a mission because the effects of crop stressors and illnesses can be reasonably localized in a place or even within an individual's plant life [2]. Accurate identification and categorization of stressors and illnesses is made possible by the precise statistics that hyper spectral photo analysis may provide regarding differences in reflectance among healthy and harmful flora. The acquisition of hyper spectral images at many wavelengths marks the beginning of the evolution of multispectral imaging [3]. By merging this data with other statistical resources, such as topography, soil composition, vegetation indices, and other spectrum records, correlations between spectral responses, stressors, and illnesses in the target area can be found. Reliable information is provided by hyper spectral photo analysis, which may help farmers make well-informed decisions on crop management [4]. These data can be utilized to identify problem locations, identify possible illnesses, and develop strategies to lessen negative effects, which will increase yield potential [5]. It is fascinating and ground-breaking to discover that hyper spectral photo analysis can be used to detect plant diseases and crop distress. It has the potential to completely transform modern agriculture by enabling farmers to anticipate crop fitness issues before they arise and support them in taking the necessary action to address them [6]. Hyper spectral picture analysis, which combines artificial intelligence with sophisticated satellite photography, is able to detect, as it should, the telltale indicators of illness and suffering in flowers. After that, models anticipating the likelihood of favorable crop fitness issues are developed using this information [7]. With these details at hand, farmers may more effectively time their spraying and planting operations to guarantee the success of their crops. Furthermore, by using this knowledge, farmers can reduce the quantity of resources required for crop production, including fertilizers, water, and insecticides, thereby lowering expenses. Additionally, research and development of new and extremely effective disorder prevention approaches may be traced back to this era [8]. This invention

*Dept. of Industrial & Management Engineering, Hanbat National University, 125, Dongseo-daero, Yuseong-gu, Daejeon, Korea, 34158 (bcmin@hanbat.ac.kr)

would help to improve crop fitness as well as lessen significant financial losses brought on by crop losses and illnesses. That is especially useful in underdeveloped nations because crop diseases are more common and their destruction has a substantial effect on people's ability to support themselves. Hyper spectral picture analysis would close the infrastructure gap that these countries often have in order to provide crop health tracking [9]. All things considered, hyper spectral photo analysis can transform contemporary agriculture by raising awareness of pressure-induced plant illnesses and crop distress. It can be applied in numerous unique areas where crop fitness is essential and provide valuable resources to both farmers and researchers [10]. It has the potential to have a very good impact on farming's future and sustainable farming methods. The main contribution of the research has the following,

* Enhance a set of guidelines for hyper spectral photo evaluation that accurately determines plant illnesses caused by strains and crop distress.
* The introduction of an automated method for the quick identification and classification of plant illnesses caused by strain and crop suffering; the use of computerized guide vector machines to advance and rectify the identification of plant illnesses caused by strain and crop suffering.

These approaches include reduced pesticide programmers, improved soil fertility control, and advanced irrigation timing. Farmers may minimize yield loss due to plant pressure and make educated decisions about crop management with the help of this evaluation.

2. Materials and Methods. A common condition brought on by fungal contamination of the wild rocket plant is early detection of a wild rocket using hyper spectral picture-based fully machine learning, which makes use of hyper spectral imaging and gadget-learning-to-know algorithms to identify the presence of the fungus [11]. The technique helps vector machines detect the fungus and determine the extent of infection by combining hyper spectral photography with algorithms such as clustering and supervised and unsupervised learning [12]. In order to reduce the disorder's impact on plant productivity, control strategies, such as implementing preventive measures or planning fungicide treatments, can be informed by this early detection strategy. Utilizing aircraft or satellite-based total stations, far-reaching sensing of biotic strains in crop blossoms helps identify the signs of biotic strains (i.e., pests or disease) in plants [13]. Using this technology, one may find the location, spread, and presence of a pest or disease inside a field. With this knowledge, the pest or disease can subsequently be controlled, for example, by using fungicides or pesticides, or by adopting other measures to stop it from spreading. Farmers can make sure they're only applying the right number of sources to solve the issue by keeping an eye on the crop's biotic pressure [14]. By reducing undesirable pests and diseases, it helps guarantee that crop output is optimized. Promising fields of disease prognosis now include superior packages of Raman and floor-greater Raman spectroscopy (SERS) in plant illness diagnosis. The analysis of plant tissue for biochemical components suggestive of vegetative diseases is becoming more and more common using these approaches. Utilizing Raman spectroscopy, researchers have identified disease-specific biomarkers from pigments and metabolites that may be present in plant tissue [15]. Similar to this, SERS has been used to examine the biochemical composition of plant tissue; yet, it works particularly well for identifying trace biochemical substances such illness-specific proteins [16]. It has been demonstrated that this approach is a kind way to identify illnesses in flowers, even in the initial stages of infection. Without the need for complicated laboratory procedures or pattern preparation, Raman and SERS spectroscopy provide quick, non-destructive, and valuable investigation of biochemical's unique to disorders. As a result, these methods are now well-known for their ability to identify early illnesses in flowers.

One way to read the effects of salinity on a wheat boom and photosynthesis is to estimate growth and photosynthetic activities of wheat grown in simulated saline subject settings using hyper spectral reflectance sensing and multivariate assessment. Wheat boom and photosynthetic qualities are measured using hyper spectral reflectance sensing, which detects the amount of light reflected off the plants over a wide range of salinity levels. The reflectance statistics are then examined using multivariate analysis to determine how salinity affects wheat growth and photosynthesis [17]. This approach has the potential to improve our understanding of how saline region conditions affect crop health and yield, as well as to develop more sensible and affordable crop management strategies to support agricultural manufacturing in these environments. A system that uses a unique imaging generation to gauge the health and growth of flora is tracking and screening plant populations using blended thermal and chlorophyll fluorescence imaging. In order to monitor changes in the flora, the imaging generation uses heat and chlorophyll fluorescence readings [18]. Stress ranges, leaf temperature, and photosynthetic efficiency can all be determined using those data. The information can be used to inform decisions about crop management, including the usage of fertilizer and irrigation. Following the thorough examination mentioned above, the following problems were found. They are,

* Limited availability of hyper spectral image data: To reliably diagnose crop distress and stress-induced plant diseases, hyper spectral image analysis needs a lot of data. It can be expensive and time-consuming to obtain hyper spectral images, which makes it challenging to gather enough information for analysis.
* Complex data analysis methods: A thorough understanding of data analysis methods and algorithms is necessary for the interpretation of hyper spectral pictures. From hyper spectral photos, crop distress and plant illnesses can be identified using complex mathematical models, statistical analysis, and pattern recognition algorithms. It is difficult for academics and practitioners without specialized knowledge to employ hyper spectral image analysis for agriculture applications because of its complexity.
* Absence of standardized protocols: At the moment, hyper spectral image analysis in agriculture lacks a standardized protocol. It can be challenging to compare and reproduce studies since different researchers and organizations may use different approaches and techniques. The broad use and integration of hyper spectral image analysis in agricultural activities is hampered by this lack of standardization.
* Dependency on ground truth data: Ground truth data is required for calibration and validation in order to correctly identify crop distress and plant diseases from hyper spectral images. However, as it necessitates physical crop inspection and sampling, gathering ground truth data can be difficult and time-consuming.

The use of hyper spectral imaging technology for precise and timely diagnosis of crop distress and stress-induced plant illnesses is what makes the research on ”Identifying Crop Distress and Stress-Induced Plant Diseases Using Hyper spectral Image Analysis” innovative. The use of hyper spectral imaging, which entails recording and analyzing a wide variety of wavelengths to gather comprehensive spectral information about an object or scene, is one of the study’s innovative features. In this study, the spectral signatures of plants under various stress circumstances are captured using hyper spectral imaging. When compared to conventional imaging methods or visual inspection, the usage of this sophisticated imaging approach provides a more thorough and accurate investigation of crop conditions.

2.1. Proposed Model. The study deals with the detection of crop distress, which is defined as any irregularity or departure from a crop’s ideal condition of health. The study intends to identify and categories several types of suffering, such as nutrient deficits, water scarcity, pest infestations, herbicide damage, or physical injuries, by analyzing hyper spectral photos. Swift and precise identification of these stressors can assist farmers in promptly implementing corrective measures, potentially reducing agricultural yield loss and maximizing resource utilization. This proposed device will be aware of crop distress and strain-caused plant diseases by employing hyper spectral image analysis. The system may be able to recognize and analyze plant life’s indicators and symptoms as needed. Images will be examined, and certain criteria will be applied to distinguish between nutritious and unhealthy crops. The system might be able to identify a wide range of indicators of crop distress, such as infections, nutritional deficiencies, and drought pressure. It will also shed light on the nature and gravity of the issue. With its comprehensive and targeted study of crop health, the tool will help farmers identify solutions and implement the best possible control measures. The computer will identify and evaluate plant life indices from field and satellite photos using device-studying algorithms.

Hyper spectral image dataset: This refers to a collection of digital images that have captured information across hundreds of narrow and continuous spectral bands [19]. These images are used to study the composition, structure, and characteristics of objects and materials on the Earth’s surface.

Separating the data: The first step in working with a hyper spectral image dataset is to separate the data into training, validation, and testing sets. This is important to ensure that the final model is trained on a diverse set of data and can perform well on unseen data.

Deep learning model: In order to analyze the hyper spectral image dataset, a deep learning model is used. This type of model uses multiple layers of artificial neural networks to learn and extract features from the images. These features are then used to classify and map the objects and materials in the images.

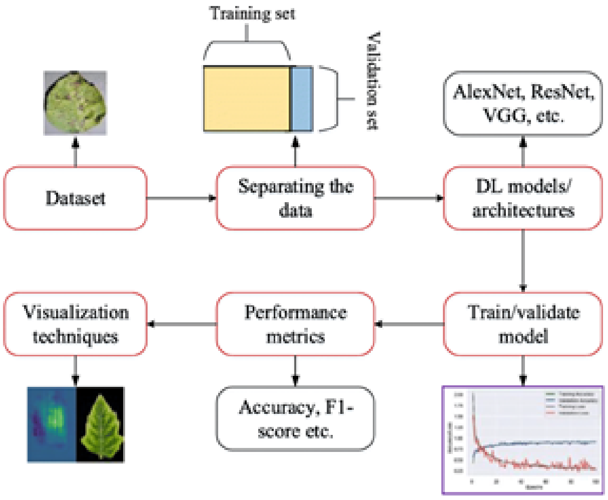

Fig. 2.1: Proposed architecture diagram

Training module: The deep learning model is trained on the training set of the dataset. During the training process, the model adjusts its parameters based on the input data in order to improve its performance and increase accuracy.

Validation module: After training the model, it is validated on the validation set. This set of data is used to evaluate the performance of the model and make any necessary adjustments before finalizing the model.

Performance metrics: To measure the performance of the model, different metrics are used such as accuracy, precision, and recall. These metrics help to assess the model's ability to correctly identify and classify objects and materials in the images.

Visualization: After the model has been trained and validated, the final step is to visualize the results. This is done by mapping the classified objects and materials back to the original hyper spectral image, creating a visual representation of the data. These visualizations can provide valuable insights and help to identify patterns and trends in the data. By following these sequential operations, hyper spectral image datasets can be effectively analyzed and used for various applications such as environmental monitoring, urban planning, and agriculture.

2.2. Pre-processing. The spectral unmixing techniques used pre-processing. This technique involves separating the mixed signals obtained from different tissues or components within an image, and then analyzing each component individually. This allows for a more accurate and detailed understanding of the underlying tissue structures and biochemical compositions, which is essential for effective disease diagnosis. Plant disease-induced stress and crop distress can be perceived by hyper spectral image analysis. Vegetation indices in the spectral indices are used to study plant fitness and cover reflectance. One such popular metric is the Inexperienced Plant Life metric.

$$P = O * \upsilon \tag{2.1}$$

$$P = \frac{1}{2} * \pi O^3 * \upsilon \tag{2.2}$$

The energy of photosynthetic interest has been measured by GVI using the near-infrared and inexperienced spectrum bands. The plant is healthier the higher its GVI value. Another widely used indicator to gauge vegetation reflectance is the Normalized Difference Plants indicator. It indicates the amount of green vegetation that is present and is far from the red and near-infrared wavelengths.

$$O_p = \sqrt{\frac{2P * \left(\frac{1}{2} * \pi O^3 * \upsilon\right)}{O}} = \sqrt{\frac{2P * \pi * O^2 * \upsilon}{3}} \tag{2.3}$$

$$O_p = 2O * \sqrt{\frac{2 * \pi P \upsilon}{3}} = P * \sqrt{\frac{2 * \pi P \upsilon}{3}} \tag{2.4}$$

Pressure and plant fitness can also be measured via hyper spectral image evaluation. For instance, a number of spectral indices, the Warmth Strain Index, and the Water Stress Index were created. Whereas the HSI gauges the temperature stress experienced by vegetation, the WSI measures the relative water content of the material in vegetation. By measuring those indices, one may build a clear picture of crop fitness.

2.3. Feature Extraction. Spectral Imaging technique used in medical imaging for capturing and analyzing detailed information about the chemical, physical, and biological properties. It involves the acquisition of multiple images at different wavelengths of the electromagnetic spectrum. The application of hyper spectral image analysis and information-driven algorithms, such as deep learning and convolutional neural networks, are covered in the paper. These algorithms are aware of plant diseases by extracting important features from hyper spectral photos of flowers and using the information to identify certain diseases and crop distress.

$$o_p = \{o_1, o_2, o_3 ......, o_a\} \tag{2.5}$$

$$p_o = \{p_1, p_2, p_3 ......, p_b\} \tag{2.6}$$

The hyper-spectral image analysis of vegetation for the purpose of identifying illnesses was done right away on two distinct types of vegetation, wheat and maize, according to the authors' documentation. The Radiometric Normalization Tree method (RN-TREE) was used to handle the data gathered from hyper spectral images measurements of diverse pressures on various plant styles.

$$DS\% = \frac{\sum Classfrequency \times scoreofclass}{tota \ln umberofplants \times Maximumscore} \times 100 \tag{2.7}$$

$$I(\theta) = \sum_i l(\hat{y}_i, y_i) + \sum_k \sigma(f_k) \tag{2.8}$$

By applying these criteria, the reflectance spectra were improved and the statistical noise and artifacts were diminished. CNNs are discussed by the writers as a means of classifying crop kinds and diagnosing diseases in the interim.

$$U = o_p + p_o \tag{2.9}$$

$$U = \{o_1, o_2, o_3 ......, o_a\} + \{p_1, p_2, p_3 ......, p_b\} \tag{2.10}$$

$$U_p = \sum_{p=1}^{\infty} o_{x(p-1)} + p_{y(p-1)} \tag{2.11}$$

The CNNs were taught to categories crop varieties and identify prompted regions using datasets produced from hyper spectral photos. It made it possible to correctly forecast the state of the tree in the image, and the authors note that the use of deep learning improved the model's accuracy

2.4. Detection. Spectral wavelength detection technique has used to detect the parts in an image. The algorithm initializes i = 0 and begins with an initial graph G0. After that, it applies the coarsening procedure and increases i by 1 to create a new, coarser graph, Gi. The graph's overall structure is maintained despite fewer vertices and edges are present thanks to the coarsening process. Next, the method determines whether the graph is sufficiently small to be divided into k subsets. If not, it moves on to the next stage, where it uses the current graph Gi to initialize a partition Pi using an initial partitioning technique.

$$p(o) = p_1(o) * p_2(o) \tag{2.12}$$

$$o(p) = o_1(p) * o_2(p) \tag{2.13}$$

The approach uses the Tubu refinement algorithm, a local search algorithm, to enhance the quality of the partition after obtaining the initial partition Pi. In order to optimize for a certain objective function, this refinement procedure iteratively shifts vertices between subsets. Subsequently, the algorithm begins the uncoarsening process by decreasing i by 1. The refined partition Pi+1 is retrieved from the coarser graph Gi using the uncoarsening function, and the Tubu refinement procedure is then applied once more to further enhance the partition quality. Until i > 0, this cycle of coarsening, first partitioning, and Tubu refinement is repeated. The method progressively returns the partition to the original network by refining it on a coarser graph generated from the previous iteration at each iteration.

$$U = \left\{ \frac{p(o) + o(p)}{o(p, o)} \right\} \tag{2.14}$$

$$U = \left\{ \frac{(p_1(o) * p_2(o)) + (o_1(p) * o_2(p))}{p(p, o) * o(p, o)} \right\} \tag{2.15}$$

Finally, when i become 0, the algorithm terminates and returns the final partition. Overall, this technique steadily reduces the size of the input graph and enhances the quality of the partition by combining coarsening, initial partitioning, and Tubu refining. While the Tubu refinement approach seeks to optimize the partition quality by iteratively moving vertices across subsets, the coarsening procedure helps to reduce computational cost by operating on a smaller graph.

2.5. Classification. A wide range of spectral band classification technique is used in hyper spectral picture analysis, which is concerned with recognizing strain-induced plant diseases and crop distress, to assess the reflectance intensity of items within the analyzed discipline scene. The discovered reflectance data is utilized to predict the kind, quantity, and presence of stress or other material that the plant and plant life are problematic for.

$$p(o) = \{O_1 * p_1(o) + O_2 * p_2(o) + ... + P_o * o_p(p)\} \tag{2.16}$$

$$o = \int_{p=1}^{o} \frac{x(p_1 * p_o)}{y(p_1 * p_o)} \tag{2.17}$$

$$o_1(p) = \left\{ \frac{x(p_1)}{y(p_1)} \right\} \tag{2.18}$$

Two key elements of the hyper spectral photo analysis system are a suitable imaging sensor and advanced processing algorithms. The computer is able to carry out a thorough assessment and evaluation of the scene since the imaging sensor records a variety of spectral bands. In reflectance mode, the spectral bands are employed to precisely quantify the light depth, producing images that contain a multitude of environmental recordings. The algorithms employed in the hyper spectral image analysis often use supervised machine learning techniques. The process entails training the algorithm on a database that contains a vast number of manually annotated samples from various spectral bands. The regions inside the picture that include stress classes are identified by the resulting classifier. It uses the reflectance reflections of the spectral bands to make a statistical classification. The proposed algorithm has shown in the following:

Proposed Algorithm	
Step.1	INPUT: HIS Images;
Step.2	INITIATE_Pre Processing ( );
Step.3	EXT_SF.Features ( ); // Extract the spatial features
Step.4	FEATURE SEL ( ); Perform feature selection
Step.5	DETERMINE_Features ( );
Step.5	COM_Spatial Correlation;
Step.6	GEN_REP_Bands;
Step.7	COM_OPT_Feature Weights;
Step.8	Begin
Step.9	If $A_b > C_b$
Step.10	$A=A_b$;
Step.11	Else
Step.12	$A=C_b$;
Step.13	End

1. Input: The first step in the sequential operation is to input the High-resolution Images (HIS Images) into the system. These images can be aerial or satellite images that capture a particular area.
2. Initiate Pre-Processing: Once the images are imported, the system will go through a pre-processing step to clean and enhance the images. This may include removing noise, correcting distortions, and adjusting the contrast and brightness.
3. Extract Spatial Features (EXT_SF): Next, the system will extract spatial features from the pre-processed images. These features are characteristics of the recorded landscape, such as land cover, land use, or terrain elevation.
4. Feature Selection (FEATURE SEL): In this step, the system will determine the most relevant features to use for the analysis. This can be based on factors such as data quality, importance, and correlation with the target variable.
5. Determine Features (DETERMINE_Features): After selecting the appropriate features, the system will use statistical or machine learning techniques to determine the specific features that contribute the most to the final analysis.
6. Compute Spatial Correlation (COM_Spatial Correlation): The system will then calculate the spatial correlation between the selected features and the target variable. This helps to identify which features have the strongest relationship with the target variable.
7. Generate Representative Bands (GEN_REP_Bands): Based on the selected features and their correlation with the target variable, the system will generate representative spectral bands that best represent the features.
8. Compute Optimal Feature Weights (COM_OPT_Feature Weights): In this step, the system will compute the optimal weights for each feature based on their importance and contribution to the target variable. These weights are crucial in determining the overall accuracy of the analysis.

Overall, this operation aims to extract, select, and compute the most relevant features and their weights to perform accurate analysis and modeling using the HIS Images.

3. Results and discussion. The device might provide a thorough examination of the entire crop development cycle, from planting to harvesting. Additionally, the system is accurate in detecting the presence of bacterial and fungal infections that affect plants. It will be able to distinguish between healthy plants and those that are afflicted with illness. Analyzing the symptoms in flowers, such as stunted growth, yellowing or

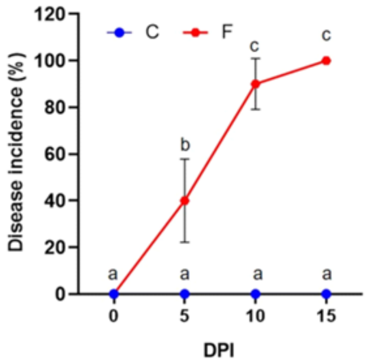

Fig. 3.1: Computation of disease incidence

withering leaves, discoloration, and more, will finish it. Consequently, farmers can also receive tips from the device regarding how to address the issue and keep it from becoming routine. Farmers will be able to use the information produced by the system to optimize their crop management techniques. It may result in increased crop fitness and yields. Here the matlab r2023 b is the simulation tool used to execute the results.

3.1. Disease Incidence. Hyper spectral photo analysis identifies plant diseases brought on by pressure and crop distress. This method is mainly predicated on the understanding that every type of crop or plant exhibits a distinct set of spectral properties. Determining the types of light that are contemplated makes it much easier to identify the existence of particular illnesses. The technique is based on spectral unmixing, which is splitting one unmarried hyper spectral image into many images representing distinct plant additives (e.g., water, additives, and chlorophyll). Fig. 3.1 shows the computation of disease incidence.

By examining each image in a sequence, spectral signatures that indicate the existence of different ranges of strain. It is also possible to determine the type and quantity of strain that is present, along with other important variables like ammonia levels and other minerals, by analyzing the spectral signature of a particular plant. In addition, the technique can identify pests and disease vectors in a specific area. In the end, hyper spectral image analysis is utilized to create predictive models that support the tracking of the overall health status of plantations and surrounding surroundings.

3.2. Selectivity (C_T). Crop monitoring is made possible via hyper spectral image evaluation for a variety of crops, including soybean, maize, and wheat. In this type of photo analysis, multiple wavelengths are tracked in order to identify exceptional compounds that enable the detection of crop illnesses and stress. It should be possible for the photo analysis to distinguish between different types of crop pressure, such as dietary stress, water loss, cold, pests, and viral or fungal diseases. Selectivity is one of the essential components of this photo evaluation. The capacity to distinguish between distinct plant forms in a picture is known as selectivity. Usually, this is accomplished by first segmenting the image into distinct classes (such as wheat, maize, and soybeans), and then use a variety of algorithms to identify the crop varieties represented in each class. Fig. 3.2 shows the computation of selectivity

Furthermore, the selection needs to take into account the fluctuations in the crop's pressure response under specific environmental variables, such as temperature, drought, and other factors. The wavelength ranges used and the spectral choice are two distinct crucial components of selectivity. Since the decision is multiplied, an outstanding photo evaluation must be able to honestly distinguish between various floral styles utilizing the spectral range. Accuracy must also increase. Along with reflectance and absorptance, selectivity also needs to take mild transmission into account.

3.3. True Positive Reflectance. The number of successful version predictions of crop distress and disease symptoms made using the Hyper Spectral photo evaluation machine is first calculated, and the number of hit predictions is then divided by the total variety of observations to determine the proper tremendous rate of

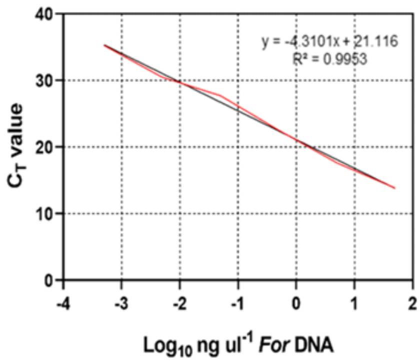

Fig. 3.2: Computation of selectivity

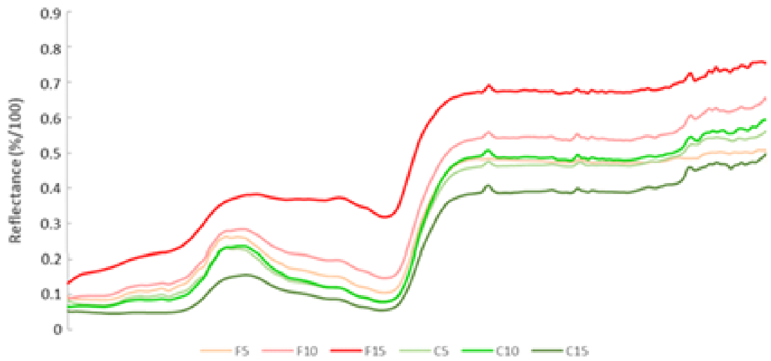

Fig. 3.3: Computation of true positive reflectance

hyper spectral image analysis used in identifying Crop distress and strain-prompted Plant sicknesses. The actual fantastic charge or percent rating is obtained by converting the achievement rate. The device has been more accurate in identifying crop distress or disease symptoms when the TPR is higher. Fig. 3.3 shows the computation of true positive reflectance.

The TPR is compared to other metrics, such as accuracy, precision, take into account, and the F1 score, in order to assess a device's correctness. The appropriate enormous fee is also employed to assess the degree to which a device misidentifies signs and symptoms of crop distress or disease. The number of times the computer correctly classifies a healthy crop as wholesome, divided by the total number of healthy plants, is the appropriate inadequate charge. This rate, which is usually given as a percentage, indicates how well the algorithm determines what constitutes a wholesome crop.

3.4. Frequency distribution. The choice of the hyper spectral photo and the degree of floor fact information accessible are the two primary factors that govern the accuracy in detecting crop distress and stress-induced plant diseases in hyper spectral image evaluation. A higher resolution yields more significant distinct information set when examining the hyper spectral pictures, which increases the likelihood of a thorough detection of agricultural distress or burdened plant infections. Fig. 3.4 shows the computation of frequency distribution.

The large range of pixels in line with inches can define and change this resolution. Usually, high-resolution photos have a pixel count of 50 or higher. Furthermore, the resolution is powered by the range of bands in the facts set. More bands imply a more remarkable designated records set, which may yield more amazing records on the scene's spectral distribution.

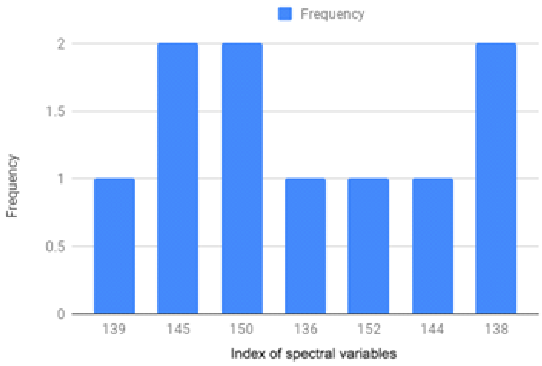

Fig. 3.4: Computation of frequency distribution

4. Conclusion. The hyper spectral image analysis will be used to diagnose plant diseases caused by strain and crop suffering. Artificial intelligence is used in this contemporary method to improve agricultural methods. This method treats flora diseases such as leaf spot, wilt, and illness-causing microbes utilizing hyper spectral recordings from crop fields. Spectral information about vegetation in the visible and near-infrared range is captured by special cameras, which are used to collect hyper spectral data. This data is then analyzed to find changes in the plant and may identify anomalies that could indicate deficiencies or illnesses. This method can assist farmers in identifying capacity problems before they cause significant harm, enabling them to address the problem promptly and boost overall yield. Additionally, this approach is economical and an excellent tool for monitoring vast areas without requiring an excessive amount of human resources.

REFERENCES

[1] Mustafa, G., Zheng, H., Li, W., Yin, Y., Wang, Y., Zhou, M., ... & Yao, X. (2023). Fusarium head blight monitoring in wheat ears using machine learning and multimodal data from asymptomatic to symptomatic periods. Frontiers in Plant Science, 13, 1102341.

[2] Chauhan, D. K. (Ed.). (2023). Beneficial chemical elements of plants: recent developments and. food processing, 54, 1215-1247.

[3] Rahman, A. N. A., AbdelMageed, M. A., Assayed, M. E. M., Gharib, H. S. A. R., Nasr, M. A., Elshopakey, G. E., ... & Ahmed, S. A. (2023). Imidacloprid induced growth, hematological, neuro-behavior, anti-oxidant, economic, genetic, and histopathological alterations in Clarias gariepinus: Alleviative role of dietary Hyphaene thebaica. Aquaculture, 564, 739058.

[4] GALLICA, T. COMPARATIVE ANALYSIS OF SALINITY TOLERANCE IN TAMARIX AFRICANA AND TAMARIX GALLICA ORIGINATING FROM TWO ITALIAN PROVENANCES.

[5] Zakrzewska, J., & Žiåić, M. Transport and metabolism of vanadium in filamentous fungi with emphasis on fungus Phycomyces blakesleeanus. In Serbian Biochemical Society Eighth Conference (p. 81).

[6] Kairuz, E., Rivero-Aragón, A., & Angenon, G. (2021). In vitro propagation and biotechnological improvement strategies of plants with high-intensity sweetener and anti-diabetic activities. In Biotechnology of Anti-diabetic Medicinal Plants (pp. 153-210). Singapore: Springer Singapore.

[7] Bodra, N. (2018). How Arabidopsis thaliana dehydroascorbate reductase 2 and mitogen activated kinase 4 cope with cysteine sulfur oxidation (Doctoral dissertation, Ghent University).

[8] Han, M., Wang, B., Song, G., & Shi, S. (2020). Comparative study of alleviation effects of DMTU and PCIB on root growth inhibition in two tall fescue varieties under cadmium stress. Ecotoxicology and Environmental Safety, 196, 110528.

[9] Smith, C. C., O'Rourke, M. B., Padula, M., De La Monte, S. M., Sheedy, D. L., Kril, J. J., & Sutherland, G. T. (2018, August). ACCURATE MASS MALDI-TOF/TOF LIPID IMAGING OF HUMAN BRAIN TISSUE. In 19th World Congress of International-Society-for-Biomedical-Research-on-Alcoholism (ISBRA). WILEY.

[10] Abbas, E. Y., Ezzat, M. I., El Hefnawy, H. M., & Abdel-Sattar, E. (2022). An overview and update on the chemical composition and potential health benefits of Opuntia ficus-indica (L.) Miller. Journal of Food Biochemistry, 46 (11), e14310.

[11] Singh, J., Pandey, A., Singh, S., Garg, V. K., & Ramamurthy, P. C. (Eds.). (2023). Current Developments in Biotechnology and Bioengineering: Pesticides: Human Health, Environmental Impacts and Management. Elsevier.

[12] Limera, C. O. (2019). Development of efficient regeneration and genetic engineering methods through organogenesis and somatic embryogenesis in prunus spp and vitis spp.

[13] Marvasti-Zadeh, S. M., Goodsman, D., Ray, N., & Erbilgin, N. (2023). Early detection of bark beetle attack using remote sensing and machine learning: A review. ACM Computing Surveys, 56 (4), 1-40.
[14] Holden, C. A. (2023). ATR-FTIR Spectroscopy-Linked Chemometrics: A Novel Approach to the Analysis and Control of the Invasive Species Japanese Knotweed. Lancaster University (United Kingdom).
[15] Carbas, B., Machado, N., Pathania, S., Brites, C., Rosa, E. A., & Barros, A. I. (2023). Potential of legumes: Nutritional value, bioactive properties, innovative food products, and application of eco-friendly tools for their assessment. Food Reviews International, 39 (1), 160-188.
[16] Jaffe, Y., Caramanica, A., & Price, M. D. (2023). Towards an antifragility framework in past human–environment dynamics. Humanities and Social Sciences Communications, 10 (1), 1-12.
[17] Singh, B. M., Dhal, N. K., Kumar, M., Mohapatra, D., Seshadri, H., & Nayak, M. (2023). Retaliation of Alstonia scholaris (L.) R. Br. to caesium and strontium in hydroponics: effect on morpho-physiology and induction of enzymatic defence. Environmental Monitoring and Assessment, 195 (6), 703.
[18] Barathi, S., Lee, J., Venkatesan, R., & Vetcher, A. A. (2023). Current Status of Biotechnological Approaches to Enhance the Phytoremediation of Heavy Metals in India—A Review. Plants, 12 (22), 3816.
[19] https://www.kaggle.com/datasets/billbasener/hyperspectral-library-of-agricultural-crops-usgs.

Edited by: Mahesh T R
Special issue on: Scalable Dew Computing for future generation IoT systems
Received: Jan 30, 2024
Accepted: May 9, 2024