Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7778236

TOMATO DISEASE RECOGNITION MODEL BASED ON HYBRID FOA-SVM CLASSIFICATION METHOD FOR INDOOR AGRICULTURAL APPLICATION

Mrs.D.Radha,
Research Scholar, Vels University, Assistant Professor, Dept. of Computer Science,
Shri Krishnaswamy College for Women, Anna Nagar, Chennai-40.
radha.aasc@gmail.com

Dr.S.Prasanna
Head Of the Department, Department of Computer Applications, VELS University
prasanna.scs@velsuniv.ac.in

Abstract: *For many individuals, one of the most significant sources of income is agriculture. The COVID-19 epidemic has also had a severe impact on conventional farming. The FAO reports that some people's access to food is being restricted by border closures, quarantines, and interruptions in supply chains, particularly in nations that have been severely affected by the virus or that already have high levels of food poverty. In 2016, the market for indoor farming technology was estimated at $23.75 billion, and by 2022, it is expected to reach $40.25 billion. When compared to traditional agricultural techniques, yields are often substantially greater. Instead of growing in only two dimensions, crops planted indoors may do so all year round, regardless of the weather outside. A key study area in smart horticulture is the intelligent diagnosis and categorization of greenhouse plant diseases. However, because plant diseases frequently arise organically, they have an impact on a lot of farmers. If necessary precautions are not followed, illnesses can be dangerous to plants and affect the productivity, quality, or quantity of the final output. Because of this, plant disease detection and prevention are major issues that should be taken into account in order to boost output. A better plant disease-recognition algorithm is required to correctly identify plant diseases under challenging environmental settings. An innovative hybrid classification system is utilised in this work to identify the tomato disease. The hybrid FOA-SVM classification method is based on Fruitfly Optimization Algorithm (FOA) & Support vector machine (SVM). The model is utilised on tomato plants for precise disease identification and improved diagnosis. For all types of plants, Support Vector Machine is shown to be the most effective classifier. The experimental findings demonstrate that our hybrid technique is more accurate than other methods already in use and has a substantial impact on the categorization of illnesses that are similar.*

Keyword: *Feature Extraction, Segmentation, Classification, SVM, FOA.*

I. INTRODUCTION

Fossil fuels, oil, natural gas, and water are among the natural resources that are rapidly running out and may soon run out. The world's resources are depleted by extensive and intensive agriculture, which uses half of the fresh water supply and wipes off a large portion of the planet's arable land. Because vertical farming consumes 95% less water than conventional farming, it is a far more enticing idea. Although this idea is not new, modern knowledge and technology have made it possible for commercial vertical farms to be deployed globally with excellent crop yields, efficient use of land, and efficient transportation [1].

Agriculture output is a crucial component of a country's economic growth. Climate has an impact on crops, which might make them more vulnerable to pathogen infection throughout the growing phase, reducing productivity. In extreme circumstances, the plants die and the leaves drop prematurely. It's important to correctly detect plant illnesses in order to lessen the financial losses brought on by those diseases. Expert diagnosis and pathogen analysis are the two techniques now in use. The former relates to plant security specialists who have years of expertise in the field and in-person investigational work determining the severity of plant lesions. This technique is sensitive to subjectivity, has a poor level of accuracy, and depends heavily on professional expertise. The latter entails cultivating and studying pathogens up close. This technique has a high rate of diagnostic accuracy, but it takes a lot of time and requires a laborious operating procedure, making it unsuitable for field detecting [2]. Plant diseases are a priority in worldwide agricultural development because they have a major impact on agricultural productivity and quality. According to statistical findings from relevant studies, at minimum 10% of the world's food output is lost due to plant diseases. The two primary issues that affect plants, their products, and their quality, particularly during the winter greenhouses planting procedure, are diseases and disorder [3].

The tomato is a significant commercial crop worldwide. It is susceptible to a wide range of illnesses, and this condition has a significant negative impact on tomato quality and output as well as leading to significant financial losses. A typical disease in tomato plants is tomato grey leaf spot, which not only kills the leaves' capacity for photosynthesis but also stunts tomato development and lowers production. Tomato grey leaf spot has become serious epidemic in the domestic tomato industrial base in recent years. Controlling the grey leaf spot disease in tomatoes is challenging. Only one vegetable that may be consumed as fruit among many other agricultural products is the tomato, and it has a considerably better nutritional content than fruit. It has a high yield, or its planting area is expanding, particularly in greenhouses where it does so quickly. However, throughout their growth, tomatoes are vulnerable to illnesses and pests, which significantly reduces their production and quality and costs farmers a tremendous amount of money [4].

Image processing methods are being used effectively to automating the process of identifying plant diseases. About three or four years ago, image processing has been more important in the field of relevant study. On the plant, a variety of illnesses are present. The identification of various illnesses is a very difficult process. Digital image processing techniques are the most important methods used for identifying and analysing plant leaf diseases. The agronomical crop photos are now being captured and transmitted to the information centre using a variety of image collecting equipment and data transmission methods. The most important procedure for learning about leaves is leaf identification. In the agricultural world, diagnosing leaf diseases is just as laborious as correctly identifying leaves. It is much easier to identify leaf diseases after the kind of leaves has been determined. Visual signs on the plant stems and leaves can be used to detect illness. The plant disease is identified by the human eye using the manual approach. However, the manual procedure takes more time and is somewhat more expensive [5]. With the use of image processing tools, the numerous investigations have been conducted and are undergoing accurate plant provides strategies [6] [7].

Plant diseases have significant detrimental effects on the quality and amount of produced goods. If these disorders are not promptly detected, there is a greater chance of food poverty. Plant diseases should be managed as much as possible to preserve crop quality since some agricultural products, like rice and maize are the most significant sources of food. Therefore, it is crucial to diagnose plant illnesses in order to ensure the proper functioning & great quality of agricultural goods [8].

When analysing plant leaf diseases, scientists and researchers were able to pinpoint the major problems and difficulties. These are a few of them:

- The quality of leaf is considered as the most important for a healthy plant.
- Require a wide dataset for processing.
- Also we require a good quality images without external noises.
- Segmentation of affected area is necessare for superior feature extraction.
- There may be some difference in leaf colout due to some environmental facts.
- Diagnosis has becam challenging as increasing in count of diseases in plants. [10]

Therefore, preventative and control plans may be developed as soon as feasible if early identification of tomato crop diseases is achievable before the widespread pandemic. It is important to take the proper precautions and to switch passive control and prevention to active controls and prevention as soon as possible. In this study, a brand-new, cutting-edge hybrid technique is employed to identify the tomato disease. The hybrid FOA-SVM classification method is built on Fruitfly optimization (FOA) & Support Vector Machine (SVM). The model is utilised on tomato plants for precise disease identification and improved diagnosis.

II. RELATED WORKS

Direct & visual monitoring by knowledgeable individuals and plant professionals has, so far, proven to be the most effective approach for identifying plant diseases. Below are some methods that highlight various plant disease detection strategies.

Convolutional neural networks are a deep neural architecture that, according to Ashutosh Kumar Singh et al. [11], has proved very successful in image identification. LeNet, ShuffleNet, AlexNet, EffNet, & MobileNet were five convolutional neural network designs that were trained and evaluated for the issue at hand. The latter had the greatest performance among them, with an efficiency of 96.1%. All networks were integrated into committees and voted on using one of three voting methods: majority, hybrid feature-based random forest, or Bayesian optimal SVM. As a consequence, their work used convolutional neural networks to identify leaf illnesses in apple, maize, potato, tomato, & rice plants with a maximum accuracy of 96.1%.

Despite their remarkable resemblance, Albert C. Cruz et al. [12] showed that it is feasible to automatically identify leaf scorching in Olea europaea L. from leaf cutting photos and that it can be distinguished from abiotic stress images. Transfer learning made it possible for deep learning to be applied despite the dearth of training instances. When it is too difficult to gather even tens or thousands of pictures typically needed for deep learning, large leaf databases like PlantVillage can be leveraged to allow deep learning for additional plant species and illnesses. Additionally, they introduced a unique context-injection algorithm for convolutional neural networks, dubbed the context injection system.

Panuwat Mekha et al. [13] described a technique that might be utilised to categorise rice leaf diseases using pictures. The most accurate technique was found to be the randomised forest method, with a classification accuracy of 69.44 percent. Their research also demonstrates the stream algorithm for classification jobs of rice leaf pathogens image analysis using knime methodology, which can be analysed and retrieved the many aspects of each approach of rice leaf disease. Also, their research provides evidence for the usefulness of each algorithm's image for diagnosing rice leaf disease.

An automated plant identification system that employs machine learning to detect illnesses in grape leaves was proposed by Jaisakthi S.M. et al. [14]. The suggested method uses the grab cut segmentation approach to first separate the leaf component from the background. Two distinct techniques are used to identify the sick area in the segmented leaves. Global thresholding is used in the first method, whereas semisupervised learning is used in the second. Texture and colour characteristics are retrieved from the diagnosed diseased portion, trained using several classifiers, and also the findings are compared. For classification, they have SVM, RF, and Adaboost methods. By utilising global thresholding and SVM, they were able to reach a superior result of 93.035% for accuracy.

Shima Ramesh et al. [15] identified anomalies on plants that happen in their greenhouses or in the wild. For accuracy, the method was compared to other ML models. The method used 160 photos of papaya leaves and a RF classifier. The classification accuracy of the method was around 70%.

A brand-new technique for handling closed & unclosed wormholes made by cabbage caterpillars on rapeseed leaves was put out by Yun Zhao et al. [16]. The process involved identifying closed wormholes, finding unclosed wormholes, and reconstructing closed wormholes. By using the hole filling function, closed wormholes were processed. A location algorithm or a reconstruction method made up the unclosed wormhole processing approach. The location factor & test function were utilised in the localization algorithm to find the bitten edge. The G-WNNRA, WNN, GNN, and BPNN algorithms were used to create system is designed and validation models. The calibration model which is based on G-WNNRA has correlation coefficient & determination coefficient of 0.998 and 0.953, which are superior than the projections based on WNN, GNN, and BPNN algorithms Consequently, the suggested left edge reconstruction approach works well.

MFO-Rough set tomato illnesses detection, a novel method for tomato disease detection, was introduced by Aboul Ella Hassanien et al. [17]. In their method, a brand-new feature selection algorithm (MFORSFS) was initially put out, put into practise, and assessed. The dimension reduction issue of the tomato illnesses detection technique is resolved by the MRORSFS, which combines the MFO with the fuzzy sets to choose the best features characterising the tomato leaves. To restrict the quantity of characteristics to those that can accurately represent each leaf of the infected tomatoes, the MFORSFS then was used to the tomatoes disease detection method. In their issue, the MFORSFS method was contrasted with selecting features based on both PSO and GA. Future applications of different parameter selection techniques for choosing the optimal parameter values might enhance their strategy. Testing their technique with a different pool of datasets that create a significant amount of issues, such as larger feature space dimensionality, more classes, and a range of data sizes, is another important factor to take into account.

An extensive overview of current scientific effort in plant disease identification utilising IPTs was provided by Lawrence C. Ngugi et al. [18]. They have shown that shallow classifiers taught with handmade features have been surpassed by DL algorithms. Deep learning algorithms are capable of accurately identifying disease and pests if there is enough data for training. It has been explored how to increase classification accuracy by gathering massive data with high variability, enhancing the data, learning transfer, and visualizing CNN activation maps.

Among others, Aravind Krishnaswamy Rangarajan [19] To classify tomato crop diseases, images from the PlantVillage dataset and pretrained DL architecture, particularly AlexNet and VGG16 net, were used. On a dataset of 13,262 images, VGG16 net's classification accuracy was 97.29% while AlexNet's was 97.49%. The performance of the method has been calculated by varying the bias and weight learning rate, the bias and minibatch size, and the number of images. The amount of photographs has a significant impact on the models' effectiveness. The accuracy is greatest when there are 373 photographs. Although there was no evident correlation between classification performance and minibatch size in AlexNet, classification accuracy decreased as the minibatch size increased in VGG16net. Similar to their, AlexNet's accuracy decreased until the parameter reached 30, and then dramatically increased, by fine-tuning the weight & bias learning rate. Accuracy dropped when the bias and weight learning rate in the VGG16 net increased. In comparison to the more complex VGG16 net, AlexNet provides respectable accuracy with a less computing load and faster execution time.

To get more precise findings, Dhaya R. et al. [20] suggested a strategy that consists of sequential stages. The two-factor identification strategy helped us get more accurate findings. Even when utilised with single-factor identification, such as using image recognition techniques or ML algorithms, a single factor people process had lower accuracy. They successfully predicted the FO illness using their suggested classifier algorithm with a high degree of accuracy.

Murali Krishnan and others, [21] Early diagnosis of plant illnesses aids in the elimination of several plant-related maladies and enhances plant development on a broader scale. A simple, cost-effective way for identifying scorch that also contributes to a decrease in manual labour in fields is the employment of clustering algorithms. The segmentation technique may be used to detect weather conditions that are harmful to plants as well as to discover illnesses in plant species that are infected by environmental factors. K means clustering, as opposed to Fuzzy C mean clustering, appears to be straightforward and efficient in identifying the contaminated region with a decreased need for human cluster selection. Before the plant's Xylem spreads the illnesses to other sections of the plant or tree as is the case with large plants or trees, the signs of infections may be easily spotted on the stem and leaves using image processing.

Joseph M. Roberts and others [33] Although pests can get into vertical farming systems, there is a unique opportunity to use cutting-edge crop protection techniques. The use of standard operating procedures (SOPs) for personnel and equipment mobility and sterility, as well as the use of high-resolution sensor-based monitoring of growth conditions, are some of the current pest and disease management methods used in vertical farms. By implementing IPM-based solutions that include artificial light-based disease behaviour change, isolation systems, pest, etc., it could be able to better their management. In order to attain maximum effectiveness while lowering the danger of insects and diseases, such procedures would need to be uniquely adapted to each vertical farm type and development level. Vertical farming systems are perfectly suited to enhanced biological control methods, just like protected horizontal farming systems.

Summary:

- It proved that SVMs might be taught to recognise minute details in high quality RGB pictures.
- Ongoing surveillance is required for early illness detection and to stop the spread of disease.
- Researchers ought to pay greater attention to identifying pests and tree diseases.

III. PROPOSED METHOD

Although the vertical farm has shown to be a reliable source of food for the planet's expanding population, danger still lurks due to the technology's youth and greater starting expenses than with other new technologies. Given that the majority of people in the world get their food from these farms, a disease pandemic might have a catastrophic impact on civilization. A disease recognition system is thus required to inform farmers of probable outbreaks. In the upcoming years, indoor systems will be used to grow the majority of vegetation and crops, however farmers won't have much room to monitor the plants grown on parallel plates. Farmers will find it simpler to identify defects and monitor the health of their plants and harvests thanks to this technology [1]. The management of pests and illnesses that injure plants through herbivory and vector plant infections is one of the long-standing problems that vertical farming encounters; if new production techniques are adopted, new obstacles will arise. While certain features of vertical farming will be familiar from protected horticulture systems that have been around for a while, others could be novel, offering new difficulties for producing healthy crops and, as a result, high-quality output. Also, because the crop selection comprises a wide range of horticultural fresh produce species, vertical farming necessitates the control of several diseases and pests [33].

It is quite difficult to identify plant diseases using photos from mobile and digital cameras. In a few chosen diseases and crops, the recent trend of using different machine learning techniques for plant disease categorization has yielded encouraging results. Pests and diseases cause crops or parts of plants to be destroyed, which lowers food output and increases food insecurity. Additionally, less developed nations have less understanding about illnesses and pest management [22]. The precision of the findings has been improved by using contemporary methods like DL and ML algorithms. Because of this, plant disease detection and prevention are major issues that should be taken into account in order to boost output. A better plant disease-recognition algorithm is required to correctly identify plant diseases under challenging environmental settings. In this study, a brand-new, cutting-edge hybrid technique is employed to identify the tomato disease. The hybrid FOA-SVM classification method is based on

Random Fruitfly Optimization Algorithm (FOA) & Support Vector Machine (SVM). The model is utilised on tomato plants for precise disease identification and improved diagnosis [23].

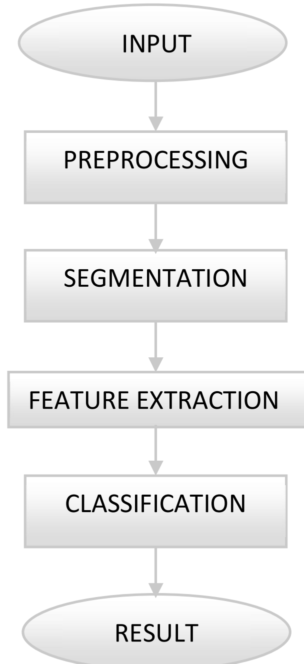

Figure1. Block Diagram

i. Dataset

The PlantVillage dataset was used to acquire the pictures for 6 distinct tomato crop illnesses and healthy samples. In the segmented pictures of the dataset utilised in this work, all background pixels in the three channels (Red, Green, and Blue) were set to 0, save for the pixel associated with leaves (as shown in Figure. 2). For the selected illnesses & strong people from the collection, a mean of 13,262 segmented pictures were available.

Figure2. (a) Healthy; (b) Late blight; (C) Leaf mold; (d) Two-spotted Spider mite attack; (e) Target spot; (f) Tomato mosaic virus disease; (g) Tomato yellow leaf curl virus disease

The growing condition of the tomato was tracked in real-time using video monitoring systems in order to confirm the accuracy of the objects detection approach for tomato pests and diseases presented in this study and to guarantee professional in the initial point of diseases & pests occurrence.

ii. Preprocessing

The margins of the tomato leaves' pixels are first eliminated. The RGB tomato leaf photos that were then obtained were scaled for 512x512 pixels. after which a hybrid thresholding was used. then comes picture modification and simple image enhancement. Images are histogram equalised in the end.

Figure3. photos that have been altered, improved, and histogram equalisation

iii. Segmentation

The leaf portion of the preprocessed picture is separated from the background picture using the Grabcut segmentation technique. This approach uses the Gaussian Mixture Models (GMM) to classify pixels as background or foreground and also uses an initial rectangle to roughly separate the two. As the bounding box, we utilised a rectangle with the dimensions (10, 10, w-30, and h-20) [14]. W and h stand for the image's width and height.

The sick sections are taken from the foreground, which is the leaf component. Lesions, coloured patches, and some yellowing leaf tissue make up the diseased portion. We have two distinct procedures for removing the infected area from the leaves.

Global Thresholding for Diseased Part Identification: In this technique, the RGB picture is transformed into a greyscale image before global thresholding is used to turn the images into binary images. Image regions labelling is used to locate the contours on the thresholded picture. Then, morphological techniques like dilation and erosion are used on the contour with the biggest area. The input image is transformed into an HSV image, then thresholding is done to the h channel. The contour detected picture and the HSV image are then both subjected to the binary AND operator. Binary inversion thresholding was used once more to threshold the resulting picture [14].

In the BGR picture, the damaged leaf tissue often has a blue tint. By turning the RGB image into a BGR image, blue colour pixels are filtered off to segment the sick portion. We have utilised the prevention or treatment to identify the bottom and upper border of blue colour pixels in order to filter those pixels. The lower and upper border pixels are then filtered out of the input image as blue pixels. Thresholding is used on the filtered picture, and then the sick regions are found.

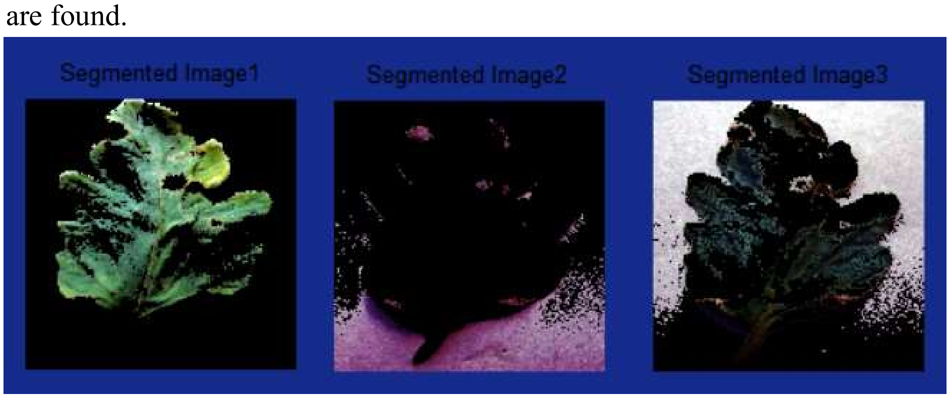

Figure 4. Segmented picture

iv. Feature Extraction

By assessing certain characteristics or attributes of each divided region, feature extraction is the process of reducing the amount of picture data [25]. Characteristics are used to describe an image's distinctive qualities. The next crucial step after picture segmentation is to identify the characteristics from the image that may be used to diagnose the illness. We employ the new feature pool, which is thoroughly explained in the following subsections.

The gray-level co-occurrence matrix is a statistical method for analysing textures that accounts for the spatial relationship between the pixels (GLCM). The GLCM functions generate a GLCM by calculating the frequency of pairs of pixels with specific values and in specific spatial relationships occurring in a picture. From this matrix, measurable metrics are then extracted to characterise the texture of the image. The graycomatrix function in MATLAB creates gray-level co-occurrence matrices by calculating how frequently a pixel with the strength (gray-level) value I occurs in a specific spatial relationship to a pixel with the value j. (GLCM). The default definitions of the spatial connection are the pixel of interest or the pixel immediately to its right (horizontally adjacent), but you may also specify additional spatial connections between the two pixels. Each element I j) in the final GLCM may be calculated by counting the number of times the input image's pixels with value I occurred in the desired spatial relation to pixels with value j [26].

An essential component of our suggested paradigm is feature extraction from a picture. The GLCM texture feature relies on the phenomenon of neighbouring grey levels occurring together and their counts in the picture. A square implements on the ROI (regional of interest) dimensions of the number of grey levels (N) in the X-ray pictures is used to create the GLCM texture feature. Twelve features in all were retrieved for this article; a description of each component is provided below.

Assume that I j are its values or the elements' coordinates in a M cooccurrence matrix of N dimensions. RMS, Variation, Smoothness, Kurtosis, Skewness, IDM, Mean, Standard Deviation, Entropy, Energy, Homogeneity, and

The method of employing statistical distributions of intensity value combinations at various points within an image to extract second order statistical texture information is widely established. Statistics come in three different orders, depending on how many intensity points are present in a picture. Though theoretically feasible, implementation of higher orders statistics is impossible owing to computational cost. Information about the structural organisation of surfaces and how they relate to their surroundings is contained in texture characteristics. We acquire a total of 22 texture-based characteristics, such as energies, correlations, volatility, inverse difference moment (IDM), uniformity, sum variation, correlation, contrasting, maximum probability, dissimilarity, and IDM normalised, among many others.

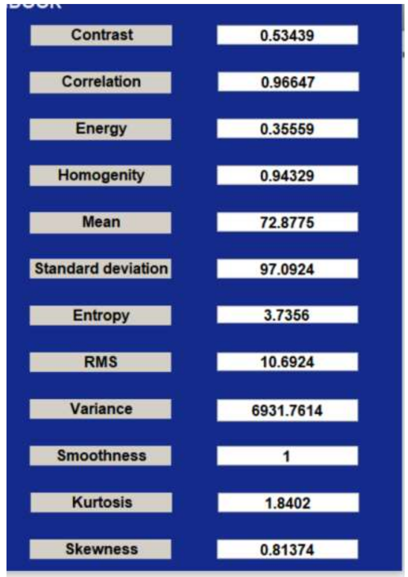

Figure 5 Simple characteristics are extracted

v. Classification

a. FOA

The swarm-intelligent algorithm is one well-liked strategy for enhancing the parameters of the clustering process. The fruit fly optimization approach (FOA) developed by Dr. Pan W. T. [27] is a novel artificially intelligent optimization technology that has been applied effectively in a number of industries [28]. The species of fruit fly possesses acute eyesight and smell. A fruit fly will always fly to where it smells a nearby food source while communicating with or learning about the location of the meal from its mates. The fruit fly uses a range of smell-based search techniques before deciding on the location with the highest scent concentration using visual search. The following are the steps of the fruit fly optimization approach. [29]:

Step 1. Initialization:

Sizepop and Maxgen, the maximum amount of iterations, are set to their initial values. randomly chooses the fruit fly population's X and Y axes in the search area.

Step 2. odor-based search method

Step 2.1. Determine each fruit fly's random distance and direction for food searching based on fragrance.

$$\begin{cases} \mathrm{Xi} = \mathrm{X} + \mathrm{R}_v \\ \mathrm{Yi} = \mathrm{Y} + \mathrm{R}_v \end{cases} \tag{1}$$

$$\mathrm{R}_v : Random\ Value$$

Step 2.2. Determine the separation (Disti) between every fruit fly or its starting point. Calculate the smell's concentration value (Si), which is equal to the square of the distance:

$$Disti = \sqrt{x_i^2 + y_i^2} \tag{2}$$

$$Si = \frac{1}{\mathrm{Disti}} \tag{3}$$

Step 2.3. To determine the scent (Smelli) of the fruit fly's location, the dominant value (Si) of fragrance is introduced into the fitness function.

$$Smelli = Fitness\ (Si) \tag{4}$$

Step 2.4. Find the ideal places for current fruit fly populations based on the best dominating value of scent.

$$[\ bestSmellbestIndex\ ] = max\ (Smelli) \tag{5}$$

Step 3. Visual-based search process. Other group members fly to the location while the best dominating quantity of smell bestSmell or its coordinate current location are kept.

$$Smellbest = bestSmell \tag{6}$$

$$\begin{cases} \mathrm{X_{axis}} = \mathrm{X(bestIndex} \\ \mathrm{Y_{axis}} = \mathrm{Y(bestIndex} \end{cases} \tag{7}$$

Step 4. Iterative optimization. Repeat steps 2 through 3 while holding onto the superior value until Maxgen is achieved in terms of iterations.

b. SVM

Training must be carried out using a model in order to increase accuracy in the capacity to make the right predictions. Support svm classifier (SVM) is a model that used train & forecast whether a picture be positive or negative on the retrieved features in the categorization of pictures. Based on traits of specified decision boundaries, SVM is a supervised model used in regression and classification. SVMs are now among the top classification model performance for a variety of classification problems [30].

SVM is currently often employed in a variety of systems for pattern recognition because it produces highly accurate classifier performance with a small amount of training data. The goal of SVM is to build a hyperplane with the best possible margins to split the input data in two groups. SVM is employed in this work to categorise the interest regions either as fire or non-fire. The SVM classification function is defined as follows:

$$f(x) = sign\left(\sum_{i=0}^{i=n} w_i . k(x, x_i) + b\right) \tag{8}$$

where the purpose of sign() is to establish if the category of x is either fire-related or not (+1 class and -1 class). The kernel's output weights are denoted by wi, a kernel function is represented by k(), and support vectors are denoted by xi and I respectively. A one-dimensional vector has been employed in our suggested strategy [31]. Since the data in this research cannot be divided linearly into two halves and no hyper-plane is known to exist, a non-linear radial basis functional (RBF) [9] is employed as follows:

$$k(x, y) = exp\left(-\frac{\|x-y\|^2}{2\propto^2}\right) \text{ for } \propto > 0 \tag{9}$$

where x, y stand for the input extracted features, and is an experimental value for the parameter regulating the breadth of the effective function f that produces satisfactory results. 500 wavelet energy from real fire footage and 500 moving pixels representing both fire and non-fire were utilised to train the SVM [32].

c. FOA-SVM

Pan proposed a new swarm-based evolutionary algorithm for global optimization called the fruit fly optimization technique, which uses fruit flies' foraging behaviour as its paradigm. The few parameters, basic structure, and simplicity of FOA make it superior to other swarm intelligence algorithms now in use. According to the ideal person who is in place at the time of each iteration, FOA also finds a better solution that is near to the perfect solution. However, unlike some other algorithms, the ABC algorithm chooses the next iteration based on the best and worst responses provided by the present user. As a result, FOA has a better probability of finding the ideal answer in general. As a result, it has recently generated a great deal of interest and has been used to effectively solve a number of optimization problems, including power load predicting, web auction logistics, partial integral derivative controller parameterization, multi-dimensional knapsack issue, steelmaking casting issue, joint replenishment problem, and unrelated parallel machine scheduling. In the optimization of multi-modal problems, the FOA algorithm, a kind of meta-heuristic approach, has the same shortcomings as other evolutionary algorithms, such as the ease with which they could enter the local optimum and occur early. To improve the performance of the original FOA's optimization, this study offers an improved fruit fly optimization technique based on SVM (FPA-SVM).

Proposed FOA-SVM Algorithm

1. 1.Input: Body X-rays, population size Iterations made and Sizepop The initial X and Y axes of a fruit fly, Maxgen.
2. Begin
3. Initial: Make the coordinate points initial.
4. X_axis = randi([imin,imax],1,1)
5. Y_axis = randi([imin,imax],1,1) % , The range of the flies is from start to maximum position.
6. dc ⟵ X_axis; k ⟵ Y_axis % Assign X_axis, Y_axis to DPC parameters.
7. Xa = X_axis + randi()
8. Ya = Y_axis + randi() % Give fruit flies arbitrary lengths and directions.
9. Calculate: Create a scent concentration array & record the test results by calculating the smell concentrations function that fits with image entropy (Smell).
10. [bestSmell,bestIndex]=max(Smell) % Using the original scent concentration, determine the extremum
11. If Smellbest>bestSmell then
12. X(bestIndex)⟶X_axis
13. Y(bestIndex)⟶Y_axis
14. Smellbest⟶bestSmell
15. End If
16. Define the SVM parameter's search range
17. Set the FOA-settings SVM's initially
18. Use the fitness equation to evaluate the fitness value.
19. Determine each particle's evolutionary component.
20. Update the state for the following generation based on the present state
21. If k = maximum iteration
22. Next, apply SVM with improved parameters.

23. If not, repeat step 17
24. End
25. Provide the segmentation result and the best parameter values.

IV. CONCLUSION

Based on methodological and technological advancements in protected growing systems, vertical farming is a distinctive technique of food production. Although conventional protected horticulture is well versed in pest and disease control, vertical farms offer new concerns that are important to the efficient operation of such systems. A deep learning architecture known as convolutional neural networks has been gaining quite notable success in the field of image identification. The best predictor for all types of plants is determined to be Random Forests. In order to identify tomato diseases, this article employs a brand-new, cutting-edge hybrid classification system. The Hybrid Technique FOA-SVM classification is built on the implant used on tomato plants for accurate disease identification and improved diagnosis, Fruit fly optimizing (FOA) but also Support Vector Machine (SVM).

Future research will build on the ideas presented here to provide an improved segmentation process for each illness category independently and calculate the intensity of the diseases that were found.

V. REFERENCES

1. Anubhove, M. S. T., Ashrafi, N., Saleque, A. M., Akter, M., & Saif, S. U. (2020, July). Machine learning algorithm based disease detection in tomato with automated image telemetry for vertical farming. In *2020 International Conference on Computational Performance Evaluation (ComPE)* (pp. 250-254). IEEE.
2. Chen, Z., Wu, R., Lin, Y., Li, C., Chen, S., Yuan, Z., ... & Zou, X. (2022). Plant disease recognition model based on improved YOLOv5. *Agronomy*, *12*(2), 365.
3. Zhang, P., Yang, L., & Li, D. (2020). EfficientNet-B4-Ranger: A novel method for greenhouse cucumber disease recognition under natural complex environment. *Computers and Electronics in Agriculture*, *176*, 105652.
4. Liu, J., & Wang, X. (2020). Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model. *Plant Methods*, *16*, 1-16.
5. Wang, X., Liu, J., & Zhu, X. (2021). Early real-time detection algorithm of tomato diseases and pests in the natural environment. *Plant Methods*, *17*(1), 1-17.
6. Krithika, N., & Selvarani, A. G. (2017, March). An individual grape leaf disease identification using leaf skeletons and KNN classification. In *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)* (pp. 1-5). IEEE.
7. Sabrol, H., & Kumar, S. (2016). Intensity based feature extraction for tomato plant disease recognition by classification using decision tree. *International Journal of Computer Science and Information Security*, *14*(9), 622.
8. Nanehkaran, Y. A., Zhang, D., Chen, J., Tian, Y., & Al-Nabhan, N. (2020). Recognition of plant leaf diseases based on computer vision. *Journal of Ambient Intelligence and Humanized Computing*, 1-18.

9. Swetha, V., & Jayaram, R. (2019, June). A novel method for plant leaf malady recognition using machine learning classifiers. In *2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 1360-1365). IEEE.
10. Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305-310.
11. Singh, A. K., Sreenivasu, S. V. N., Mahalaxmi, U. S. B. K., Sharma, H., Patil, D. D., & Asenso, E. (2022). Hybrid feature-based disease detection in plant leaf using convolutional neural network, bayesian optimized SVM, and random forest classifier. *Journal of Food Quality*, *2022*, 1-16.
12. Cruz, A. C., Luvisi, A., De Bellis, L., & Ampatzidis, Y. (2017). Vision-based plant disease detection system using transfer and deep learning. In *2017 asabe annual international meeting* (p. 1). American Society of Agricultural and Biological Engineers.
13. Mekha, P., & Teeyasuksaet, N. (2021, March). Image classification of rice leaf diseases using random forest algorithm. In *2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering* (pp. 165-169). IEEE.
14. Jaisakthi, S. M., Mirunalini, P., & Thenmozhi, D. (2019, February). Grape leaf disease identification using machine learning techniques. In *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)* (pp. 1-6). IEEE.
15. Ramesh, S., Hebbar, R., Niveditha, M., Pooja, R., Shashank, N., & Vinod, P. V. (2018, April). Plant disease detection using machine learning. In *2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C)* (pp. 41-45). IEEE.
16. Zhao, Y., He, Y., & Xu, X. (2012). A novel algorithm for damage recognition on pest-infested oilseed rape leaves. *Computers and electronics in agriculture*, *89*, 41-50.
17. Hassanien, A. E., Gaber, T., Mokhtar, U., & Hefny, H. (2017). An improved moth flame optimization algorithm based on rough sets for tomato diseases detection. *Computers and Electronics in Agriculture*, *136*, 86-96.
18. Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2021). Recent advances in image processing techniques for automated leaf pest and disease recognition–A review. *Information processing in agriculture*, *8*(1), 27-51.
19. Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop disease classification using pre-trained deep learning algorithm. *Procedia computer science*, *133*, 1040-1047.
20. Dhaya, R. (2020). Flawless identification of fusarium oxysporum in tomato plant leaves by machine learning algorithm. *Journal of Innovative Image Processing (JIIP)*, *2*(04), 194-201.
21. Krishnan, M., & Sumithra, M. G. (2013, November). A novel algorithm for detecting bacterial leaf scorch (BLS) of shade trees using image processing. In *2013 IEEE 11th Malaysia International Conference on Communications (MICC)* (pp. 474-478). IEEE.

22. Basavaiah, J., & Arlene Anthony, A. (2020). Tomato leaf disease classification using multiple feature extraction techniques. *Wireless Personal Communications*, *115*(1), 633-651.
23. Dhingra, G., Kumar, V., & Joshi, H. D. (2019). A novel computer vision based neutrosophic approach for leaf disease identification and classification. *Measurement*, *135*, 782-794.
24. Hatuwal, B. K., Shakya, A., & Joshi, B. (2020). Plant Leaf Disease Recognition Using Random Forest, KNN, SVM and CNN. *Polibits*, *62*, 13-19.
25. Mall, P. K., Singh, P. K., & Yadav, D. (2019, December). Glcm based feature extraction and medical x-ray image classification using machine learning techniques. In 2019 IEEE Conference on Information and Communication Technology (pp. 1-6). IEEE.
26. Kumar, D. (2020). Feature extraction and selection of kidney ultrasound images using GLCM and PCA. Procedia Computer Science, 167, 1722-1731.
27. Zhu, H., He, H., Xu, J., Fang, Q., & Wang, W. (2018). Medical image segmentation using fruit fly optimization and density peaks clustering. Computational and mathematical methods in medicine, 2018.
28. Huang, C., Li, X., & Wen, Y. (2021). AN OTSU image segmentation based on fruitfly optimization algorithm. Alexandria Engineering Journal, 60(1), 183-188.
29. Ding, G., Dong, F., & Zou, H. (2019). Fruit fly optimization algorithm based on a hybrid adaptive-cooperative learning and its application in multilevel image thresholding. Applied Soft Computing, 84, 105704.
30. Mahmoud, M. A. I., & Ren, H. (2019). Forest fire detection and identification using image processing and SVM. Journal of Information Processing Systems, 15(1), 159-168.
31. Mustafa, S., Dauda, A. B., & Dauda, M. (2017, October). Image processing and SVM classification for melanoma detection. In 2017 international conference on computing networking and informatics (ICCNI) (pp. 1-5). IEEE.
32. Chandra, M. A., & Bedi, S. S. (2021). Survey on SVM and their application in image classification. International Journal of Information Technology, 13, 1-11.
33. Roberts, J. M., Bruce, T. J., Monaghan, J. M., Pope, T. W., Leather, S. R., & Beacham, A. M. (2020). Vertical farming systems bring new considerations for pest and disease management. *Annals of Applied biology*, *176*(3), 226-232.