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Particle Swarm Optimization and Ensemble Learning based Apple Leaf Disease Detection

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Abstract --This work describes the use of a Particle Swarm Optimisation (PSO) feature selection and an ensemble learning classifier for the detection of illnesses in Apple leaf samples. PSO feature selection is used to select the most informative features from the dataset, which are then used as inputs to the ensemble learning classifier. K-Nearest Neighbour, Naive Bayes, and Support Vector Machine are the three individual classifiers that make up the ensemble learning classifier. The outcomes of the experiments show that the proposed approach has the capability of reaching an accuracy of 96%, which is better than the results obtained with the individual classifiers. This work is significant in terms of its influence on the growth of efficient and reliable disease detection systems in agriculture.

Keywords: - Apple leaf diseases, of Particle Swarm Optimization (PSO), Ensemble learning classifier.

I. INTRODUCTION

The rising prevalence of plant diseases has been a significant concern for the global agricultural industry. Various environmental factors, such as fungal or bacterial infections, insect infestations, and unfavorable climatic conditions, cause plant diseases. In order to ensure the health of the plants and prevent the disease's propagation, it is crucial to detect and identify these diseases in a timely manner.[1]Particle Swarm Optimization (PSO) and Feature Selection (FS) are two crucial techniques for detecting and diagnosing plant diseases. PSO is a computational intelligence method that utilizes a swarm of particles to explore a search space and identify the optimal solution to a given problem. Selecting the most relevant and useful characteristics of a dataset is the process of FS, which helps simplify the issue and boost the reliability of the findings.[2]

It has been determined that the combination of PSO and FS is effective for detecting and diagnosing apple leaf diseases. This is because the combination of PSO and FS can improve the accuracy and efficacy of disease diagnosis by reducing the dataset's dimensionality and concentrating on the most pertinent features. PSO can also be used to optimize the FS algorithm's parameters, thereby enhancing its efficacy.[3] In addition to improving accuracy,

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PSO may be used to lessen the computing burden of the issue. In order to identify and diagnose apple leaf diseases, combining PSO with FS is an effective strategy. This is because combining the two methods may simplify the solution and improve the reliability of the findings. In addition, the combination of PSO and FS can reduce the computational cost of the problem and enhance the diagnostic efficacy.[4]

There is little doubt that the incidence of apple diseases causes a decrease in both apple output and quality. It is vital to study the process of automated detection and identification of apple illnesses. Monitoring big apple fields using machine learning-based disease detection and identification algorithms has proved effective, yielding insights into the early treatment of apple diseases. Disease detection and identification are the initial steps in apple disease management. The leaves of an apple tree are many, spread out across much of the tree, & are the most noticeable part of the tree.[5] Due to the fact that the vast of apples maladies can be identified by their leaf abnormalities, Our research is limited to apple leaves, not the full apple tree. Currently, the most common method for detecting and identifying apple diseases is the visual observance of cultivators or experts in the field [20].

However, manual apple disease identification is costly, ineffective and hard to do. It is well knowledge that human eyesight has inherent limits, and as a consequence, people can't notice subtle variations in the diseased areas of leaves. However, the colour shifts in leaves that can be attributed to different leaf diseases are usually quite subtle [19]. Long-term failure to implement an accurate and quantitative method for symptom description may lead to a muddled standard for judging apple diseases, which may result in the mindless application of pesticides and the severe contamination with respect to agricultural commodities, soil, and water. In the realm of computer vision, one of the most essential jobs is feature extraction, also referred to as dimensionality reduction. Since apple diseases may generate a broad variety of symptoms on the leaves, many pattern recognition specialists are interested in image processing and recognising sick leaves. In the framework of studying how to use computer vision algorithms to recognise and diagnose images of damaged leaves on plants, this is done [6]. Diseased leaves of a plant generally seem different in colour, texture, and shape than the healthy leaves, which may be used as a diagnostic indicator. This difference can occur after an infection has taken place. There have been numerous methods proposed for plant disease recognition thus far. Using colour, shape, and texture, calorimetry has been utilised by some researchers to differentiate between healthy and diseased tissue [21]. The accuracy of apple disease detection suffers if just one of colour, shape, or texture is used as a criterion. Image features including form, texture, and color have recently been employed for disease diagnosis on apple leaves. In this work, we were motivated by this observation to develop a technique for the detection of apple illnesses via the use of image processing and a pattern recognition algorithm applied to photographs of apple leaves, with 38 characteristics related to colour, texture, and form being retrieved from each photograph of a diseased region.[7]

II. MATERIALS & METHODS

A. Feature Extraction

Due to the complexity, variety, and irregularity of the diseased leaves and spot pictures, image-processing methods were used to the collected data in order to extract the essential elements for further disease type identification. Ninety data points were used in the experiment, with 30 samples of Leaf material obtained for each disease (powdery mildew, mosaic, and rust).

B. Color features extraction

Colour in an image may be described in a variety of ways, such as the RGB colour model's red, green, blue components or the HSI colour model's hue, intensity, and saturation dimensions. The HSI colour model is widely used because it is grounded on human perception. By fusing the RGB model with the HSI model, we can determine the precise hue that represents a speck of apple leaf disease. In the RGB colour space, red, green, and blue each have their own letter code for their corresponding brightness levels (R, G, and B) [8].

The RGB model is normalized so that it is independent of the lighting conditions, which helps to reduce error. The spot area color picture may be used to extract color characteristics in RGB and HSI color spaces. The average, correlation, deviation, and energy of RGB and HSI spaces are all examples of these characteristics. Nine average parameters (R, G, B, r, g, b, H, I, and S) were calculated for each spot image [9]. In addition, we utilised the following method to calculate the colour characteristics that may distinguish between the various illnesses, taking into account the statistical aspects of variance, skewness, peak value, energy, and entropy of hue H.

$$b_k = 1/\delta^3 \sum_{b=1} (b - \bar{b}^{3}) p(b)$$

$$\delta^2 = \sum_{b=1} (b - \bar{b}^{2}) p(b)$$

$$b_F = 1/\delta^4 \sum_{b=1} (b - \bar{b}^{4}) p(b) - 3 \qquad (1)$$

$$b_N = \sum_{b=1} [p(b)]^2$$

$$b_g = \sum_{b=1} p(b) 1g[p(b)]$$

Where, $p(b) = H(b) / A_0$ is grey level; $H(b)$ is the histogram of the diseased leaf spot; A_0 is the area of the spot, cm^2; $\bar{b} = \sum_{b=1} bp(b)$ is mean value; d is variance; b_K is skewness; b_F is peak value; b_N is energy; b_E is entropy.

Based on this evaluation, the colour feature parameter for the illness spot is given as the mean of nine colour components and five statistical characteristics related to the hue H.

C. Shape features extraction

The shape of an infected apple leaf disease indication is crucial in diagnosing the condition. The foliage of the apple disease is an excellent example of how dramatically different the forms of various illnesses may be. The edge, area, and shape properties of the desired disease spot were obtained after edge extraction & spot segmentation of the picture of the sick leaf were performed. This was followed by the extraction of the shape characteristics of the target disease spot. Instead of relying on the absolute value of the distinguishing characteristics as proof of classification, it is more acceptable to evaluate the relative significance of these qualities [10]. The disease spot's outline provides a useful means of characterizing its shape; from this, one can derive the geometric features of four relative values that may be thought of as disease spot shape features; these values are the circularity of the selected disease spot area (SCIR), eccentricity (SECC), shape complexity (SCOM), and shape parameter (SFAC). The disease spot outline can also be used to determine the disease spot shape features. Following are the equations:

$$S_{CIR} = R_{incircle} / R_{excircle}$$

$$S_{ECC} = Length_{long} / Length_{short} \qquad (2)$$

$$S_{COM} = (Perimeter)^2 / Area$$

$$S_{FAC} = 4\pi Area / (Perimeter)^2$$

Both the inscribed and circumscribed radii of the affected area are denoted by the symbols Rexcricle. The long and short lengths, as well as the disease spot's perimeter and field area, are denoted by the Length and Length long and Perimeter fields, respectively.

By comparing the inscribed & circumscribed radii, we may determine the degree of circularity. The eccentricity of a disease region is the ratio of its long axis to its short axis and is a measure of its compactness. Increasing the value increases the target shape's complexity [11], which is described by its perimeter per unit area, area complexity, and dispersion degree. If the condition area's boundary is smooth and round, the value of the shape parameter, which indicates how near an item is to being round, will be 1 if all other circumstances stay the same. Closeness to round is 1, and all other instances are less than 1, whereas the value decreases as the illness spot arrangement becomes more asymmetrical.

D. Texture features extraction

Usually, the texture of diseased apple leaf tissue differs from that of healthy leaves. Spatial gray-level dependency matrices (SGDM) are a statistical approach for characterising form by sampling the way in which particular gray-levels occur in relation to other gray-levels; they may be used to infer textural features based on co-occurrence, such as colour. SGDM determines the likelihood that a pixel will be situated at a certain distance and orientation based on the grey level of the neighboring pixel. The grayscale value of the first pixel is used for this purpose. The matrices are represented by the function p (i, j, d), where i is the grayscale value at the given coordinates (x, y), and j is the grayscale value at the given distance (in degrees) from the given position (in degrees, orientation). We refer to this operation as the p-function. Once the RGB spot image has been converted to greyscale, we can create four grey level co-occurrence matrices for the spot image's directions at 0 degrees, 45 degrees, 90 degrees, as well as 135 degrees. When creating the grey level co-occurrence matrix, the texture characteristics will change based on the value of the distance parameter d. Alterations to the texture's description are always going to be brought about by the various texture attributes [12].

Because of this, determining the best possible value for the distance parameter d is of the utmost importance. If the distance parameter is set to a value that is very great, the pixel information that exists between different shades of grey will be lost, and some grayscales will not be available [13]. If the distance value is set too low, the text characteristics will overlap, which will make the load of computation much greater. We decided to use 20 pixels as the value for the distance parameter d so that the overall equilibrium would be maintained. The formula p (i, j, d,) is used to extract five statistical texture characteristics from each matrix. TCON, TCOR, TENE, TINV, and TENT are the contrasts of disease area, correlation, energy, and entropy, respectively. More information on these features may be found below. Therefore, a vector of distinct textures is made up of twenty defining characteristics of texture.

$$T_{CON} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2 p(i,j,d,\theta)$$

$$T_{COR} = \sum_{I=0}^{L-1}\sum_{J=0}^{L-1}\frac{(I-\mu_x)(J-\mu_y)p(i,j,d,\theta)}{\sigma_X\sigma_Y}$$

$$T_{ENE} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p^2(i,j,d,\theta) \qquad (3)$$

$$T_{LVN} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{p(i,j,d,\theta)}{1+(i-j)^2}$$

$$T_{ENT} = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j,d,\theta)\log[p(i,j,d,\theta)]$$

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Where μx and μy are means and σx and σy are variances, p(i, j) is a co-occurrence matrix of grey levels, i and j are pixel grey values, and L is the image's grayscale. For a discussion of the physical relevance of the formula.

E. Feature Selection

A selection of characteristics that best characterize the underlying data may be determined using Particle Swarm Optimization (PSO), an optimization approach. Particle swarm optimization (PSO) uses particles that interact with each other as well as their environment to choose the best course of action. PSO's primary advantage is that it is a basic, easily implemented algorithm that can be applied to any problem involving feature selection [14].

Each feature is represented by a particle in particle swarm optimization, and the problem is solved by optimizing the fitness of the feature set. Typically, the fitness of a feature set is defined as a cost function, which is a measure of the feature set's quality. There are numerous methods for determining the suitability [15] of a feature set, including accuracy, precision, recall, and F-measure. The cost function for PSO feature selection is:

$$F(p) = \sum g(x) + \sum h(x)$$

Where, g(x) is the fitness of the feature set

h (x) is the complexity of the feature set

P is the vector of feature weights

The goal of PSO is to minimize the cost function F(P). The steps for PSO feature selection can be summarized as follows:

- Initialize the population of particles.
- Evaluate the fitness of each particle.
- Update the velocity and position of each particle based on the local and global best solutions.
- Repeat steps 2 and 3 until the termination condition is met.
- Choose the best solution based on the fitness value.

PSO is a simple algorithm that can be applied to any problem involving feature selection. In addition, PSO's computational complexity is linear, making it appropriate for large datasets and complex problems. Incorporating various parameters such as inertia weight and acceleration constants can enhance the efficacy of PSO [16].

PSO is a highly effective optimization method that can be used for feature selection. This algorithm is simple, straightforward to implement, and applicable to any problem involving feature selection. In addition, the efficacy of PSO can be enhanced by integrating parameters such as inertia mass and acceleration constants [17].

It is possible to think of the PSO fitness function as being equivalent to the quality value of correlation feature selection (CFS). Based on the following premise, CFS is a useful measure for doing an evaluation of a selected group of features: The good feature subset is made up of characteristics that have a strong correlation with the classification but have little to no correlation with any of the other features [18]. CFS uses the merit value to identify, given a feature subset S that contains k characteristics, the ideal feature subset to forecast the class and the correlation between the features in the subset, as described below:

$$M = \max_{S_k} \frac{k r_{cf}^{-}}{\sqrt{k + k(k-1) r_{ff}^{-}}}$$

Where r_{ff}^{-} is the average correlation between features, and r_{ff}^{-} is the average correlation between features and classes.

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The correlation between two feature vectors X and Y is computed as follows:

$$r_{xy} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)}\sqrt{E(Y^2) - E^2(Y)}}$$

This research enables us to choose an appropriate feature subset for apple leaf disease identification by combining the CFS and PSO. This selection of characteristics has the best overall predictive power for the apple illness class & the lowest inter-feature correlation.

III. RESULTS & DISCUSSION

The below figure is the comparison plot of feature selectin techniques.

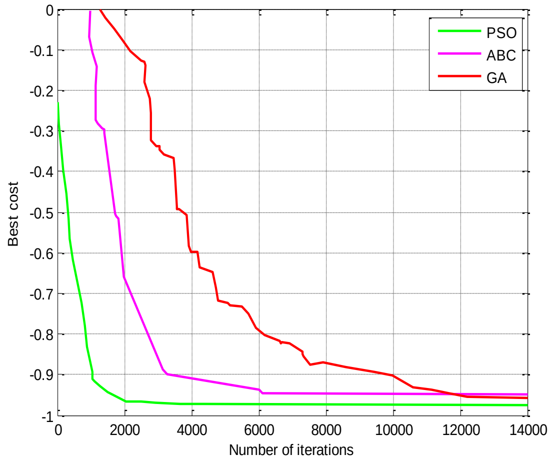

Figure 1 Best cost vs iterations

It is clear from the illustration that the PSO achieves the best value and fastest convergence to the optimum solution compared to the other bioinspired optimisation methods tested. *With Feature Selection*

The graph below depicts accuracy, specificity, sensitivity, four algorithms, with the x-axis representing the proposed and current method with feature selection and the y-axis representing the Performance Metrics values. SVM has accuracy of 92.2%, Specificity of 92.8%, sensitivity of 88%. Navies Base has accuracy of 94.2%, Specificity of 94.3% and Sensitivity of 92.59%, KNN method has accuracy of 97.9%, specificity of 96.9% and sensitivity of 1% and Ensemble Learning has accuracy of 93.1%, specificity of 93.75% and sensitivity of 90.91% as shown in the above graph.

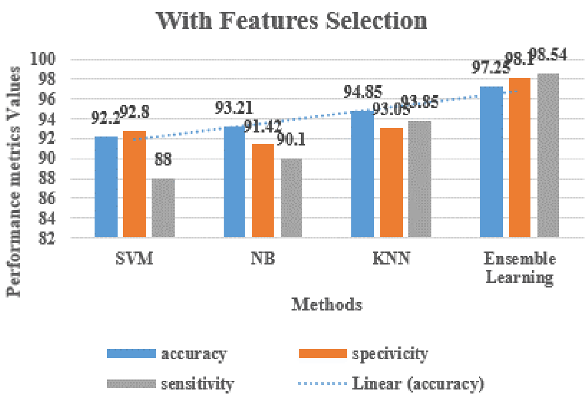

Figure 2 Performance metrics with feature selection

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SVM:

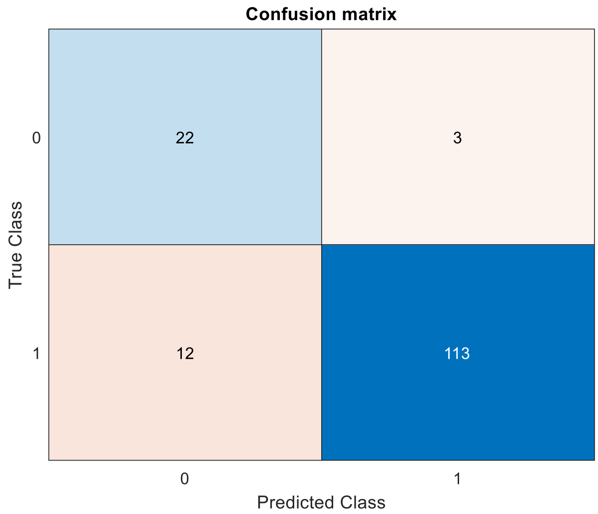

Figure 3 Confusion matrix of SVM classifier

The preceding illustration showed the confusion matrix for disease detection in Apple leaves using SVM and feature selection. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The SVM model properly predicted 113 times as diseased apple leaf and 22 times as non-diseased apple leaf. Moreover, fifteen misclassifications have occurred.

Navies-Base:

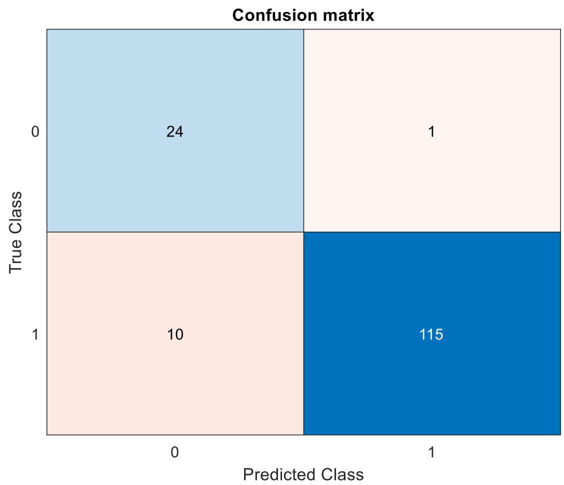

Figure 4 Confusion matrix of Navies base classifier

You can see the confusion matrix for identifying Apple leaf diseases using Navies Base and feature selection in the above figure. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The Navies Base model properly predicted 115 times as diseased apple leaf and 24 times as non-diseased apple leaf. Moreover, eleven misclassifications have occurred.

KNN:

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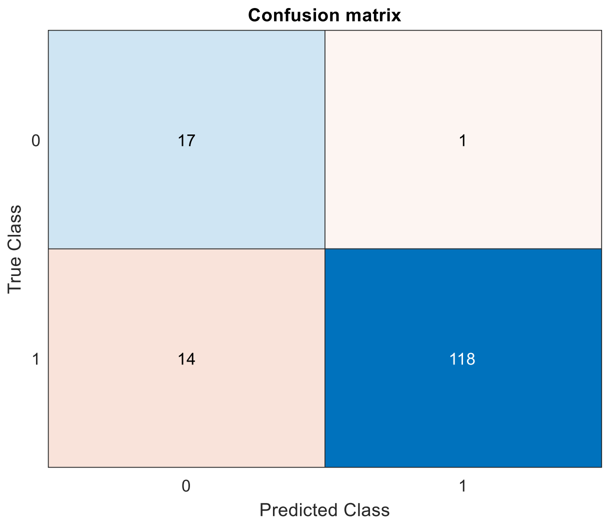

Figure 5 Confusion matrix of KNN classifier

The confusion matrix for apple leaf disease was shown in the figure identification using KNN with feature selection. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The KNN model properly predicted 118 times as diseased apple leaf and 17 times as non-diseased apple leaf. Moreover, fifteen misclassifications have occurred.

Ensemble Learning:

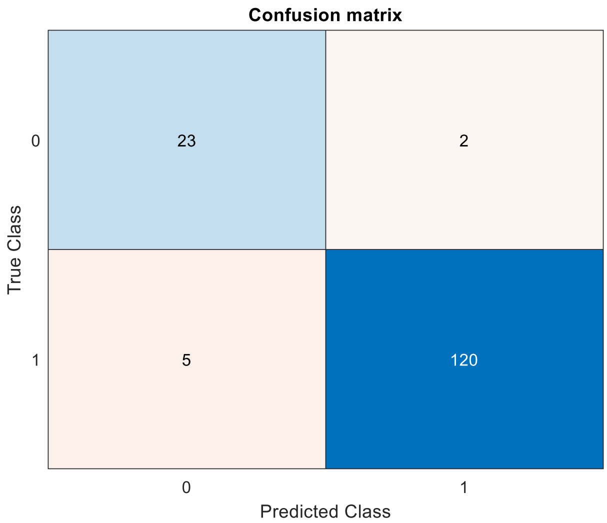

Figure 6 Confusion matrix of Ensemble learning classifier

You can see the confusion matrix for identifying Apple leaf diseases using Ensemble Learning and feature selection in the above figure. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The Ensemble Learning model properly predicted 120 times as diseased apple leaf and 23 times as non-diseased apple leaf. Moreover, seven misclassifications have occurred.

Without Feature Selection:

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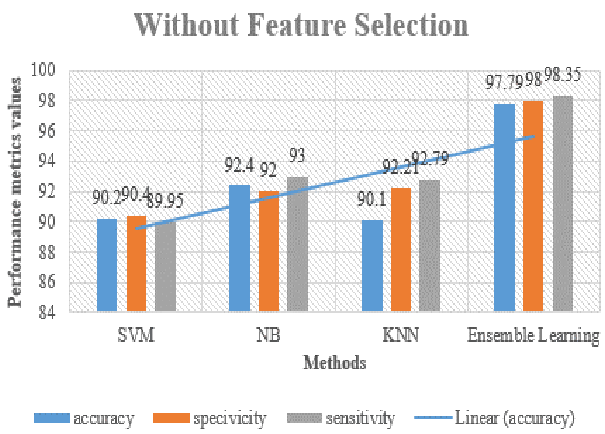

Figure 7 Performance metrics without feature selection

On the x-axis is the proposed and existing technique without feature selection, and on the y-axis are the values of the Performance Metrics; the above graph illustrates accuracy, specificity, sensitivity, and four algorithms. SVM has accuracy of 90.2%, Specificity of 90.4%, sensitivity of 89.95%. The following graph shows that the accuracy, specificity, and sensitivity for Navies Base are 92.4%, 92%, and 93% respectively; the KNN approach is 90.1%, 89.39%, and 92.54%; and the accuracy, specificity, and sensitivity for Ensemble Learning are 98.79%, 99.21%, and 99.5% respectively. *SVM:*

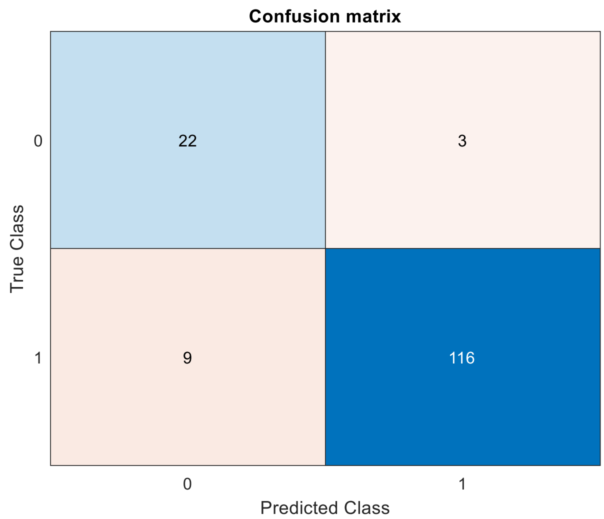

Figure 8 Confusion matrix of SVM classifier

The above picture depicted the confusion matrix for identifying Apple leaf diseases using SVM without feature selection. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The SVM model properly predicted 116 times as diseased apple leaf and 22 times as non-diseased apple leaf. Moreover, twelve misclassifications have occurred.

Navies-Base:

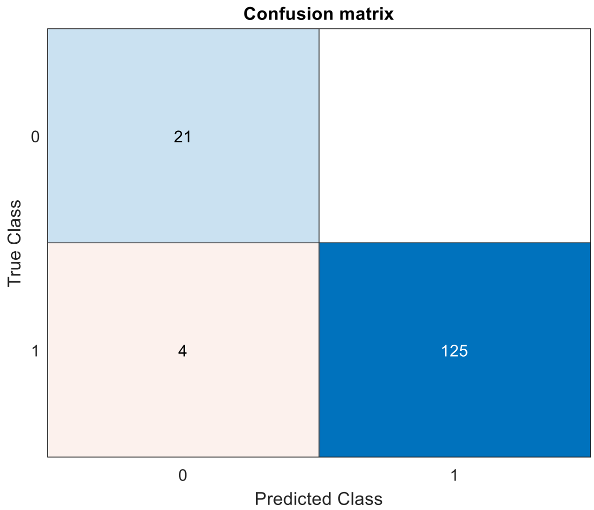

Figure 9 Confusion matrix of Navies base classifier

Apple leaf disease diagnosis using Navies-Base without feature selection was shown in the above figure as a confusion matrix. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The SVM model properly predicted 126 times as diseased apple leaf and 21 times as non-diseased apple leaf. Moreover, four misclassifications have occurred.

KNN:

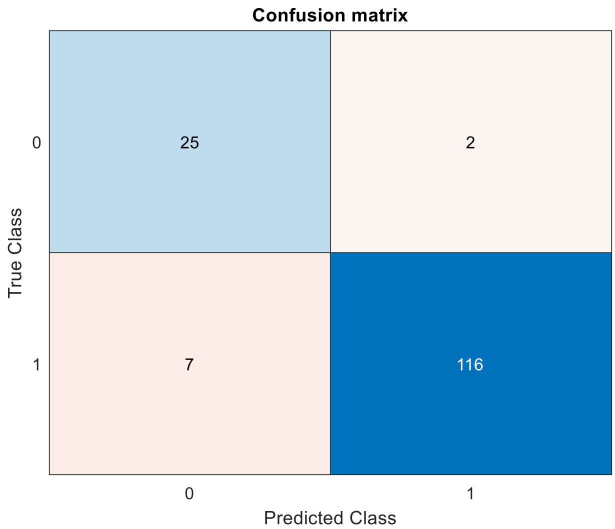

Figure 10 Confusion matrix of KNN

Apple leaf disease diagnosis using KNN without feature selection was shown in the above figure as a confusion matrix. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The KNN model properly predicted 116 times as diseased apple leaf and 25 times as non-diseased apple leaf. Moreover, nine misclassifications have occurred.

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Ensemble Learning:

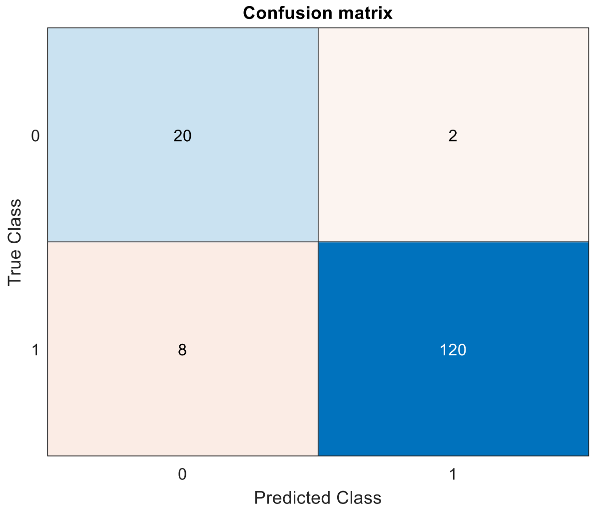

Figure 11 Confusion matrix of Ensemble learning classifier

You can see the confusion matrix for identifying Apple leaf diseases using Ensemble Learning without feature selection in the above figure. Class 0 in the confusion matrix represents a healthy apple leaf, whereas class 1 indicates a damaged apple leaf. The Ensemble Learning model properly predicted 120 times as diseased apple leaf and 20 times as non-diseased apple leaf. Moreover, ten misclassifications have occurred.

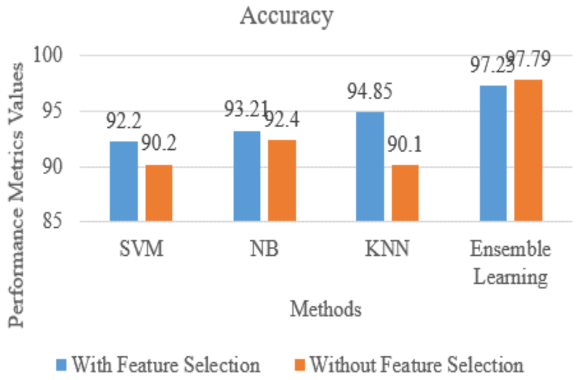

Figure 12 Accuracy

In the above graph, the x-axis displays the proposed and existing approach with feature selection and without feature selection, and the y-axis depicts the values of the Performance Metrics used in the accuracy research of the four algorithms. Ensemble Learning has an accuracy of 97.25% without feature selection method and 97.79% with feature selection method. The KNN has 94.85% accuracy with feature selection and 90.1% without feature selection. The Gaussian Navies base has a 93.21% accuracy with feature selection and 92.4% without feature selection method. The SVM has a 92.2% specificity with feature selection and 90.2% without feature selection method. Compared to the Support Vector Machine, the recommended voting classifier Ensemble Learning has an accuracy of 97.79%. When compared to other algorithms, Ensemble learning appears to Produce better results.

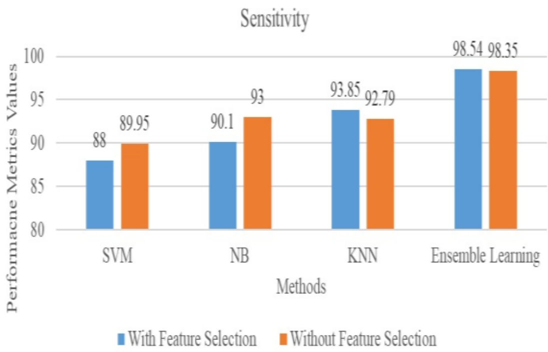

Figure 13 Sensitivity

The following graph displays a sensitivity analysis of four algorithms, where the x-axis shows the proposed and existing approach with and without feature selection, and the y-axis shows the values of the Performance Metrics. Ensemble Learning has a sensitivity of 97.25% without feature selection method and 97.79% with feature selection method. The KNN has 94.85% specificity with feature selection and 90.1% without feature selection. The Gaussian Navies base has a 93.21% sensitivity with feature selection and 92.4% without feature selection method. The SVM has a 92.2% sensitivity with feature selection and 90.2% without feature selection method. The sensitivity of the suggested voting classifier Ensemble learning is 97.79%, while the support vector machine has a sensitivity of 92.2%. When compared to other algorithms, Ensemble learning appears to produce better result

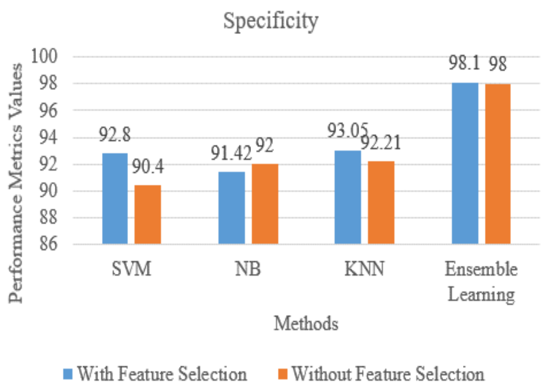

Figure 14 Specificity

Specificity results for four algorithms are shown in the above graph, with the x-axis indicating the proposed and existing technique with feature selection and without feature selection, and the y-axis indicating the values for the Performance Metrics. Ensemble Learning has a specificity of 98% without feature selection method and 98.1% with feature selection method. The KNN has 93.05% specificity with feature selection and 92.21% without feature selection. The Gaussian Navies base has a 91.42% specificity with feature selection and 92% without feature selection method. The SVM has a 92.8% specificity with feature selection and 90.4% without feature selection method. Ensemble learning, the recommended voting classifier, has a specificity of 98.1%, whereas support vector machine only achieves a specificity of 92.8%. In comparison to other algorithms, Ensemble learning produces better results.

IV. CONCLUSION

Choosing features using Particle Swarm Optimisation (PSO) is a fast and accurate way to detect Apple leaf disease. It is capable of selecting the most pertinent features from a large dataset and reducing computational expense. This method has been effective in identifying the

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essential characteristics within the datasets and has produced accurate results. Additionally, it can detect Apple leaf disease with high precision. Consequently, PSO feature selection is an efficient and effective method for detecting Apple leaf disease.

REFERENCES

1. Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui and C. Jia, "Apple leaf disease identi fication using genetic algorithm and correlation," *International Journal of Agricultura l and Biological Engineering*, vol. *10*, no. *2*, pp. 74–83, 2017.
2. Bhat, K. A., Peerzada, S. H., & Anwar, A. (2015). Alternaria epidemic of apple in Kashmir. African Journal of Microbiology Research, 9(12), 831-837.
3. Z. Peng, L. Gang, L. Minzan and L. Daoliang, "Management information system for apple diseases and insect pests based on GIS," *Transactions of the Chinese Society of Agricultural Engineering*, vol. *22*, no. *2*, pp. 150–154, 2006.
4. Mokhtar U, Ali MA, Hassenian AE, Hefny H. Tomato leaves diseases detection approach based on support vector machines. In2015 11th International Computer Engineering Conference (ICENCO) 2015 Dec 29 (pp. 246-250). IEEE.
5. Raza, S. E. A., G. Prince, J. P. Clarkson, and N. M. Rajpoot. 2015. Automatic detection of diseased tomato plants using thermal and stereo visible light images. Plos ONE 10: e0123262.
6. Y. Atoum, M. J. Afridi, X. Liu, J. M. McGrath and L. E. Hanson, "On developing and enhancing plant-level disease rating systems in real fields," *Pattern Recognition*, vol. *53*, no. *5*, pp. 287–299, 2016.
7. P. R. Rothe and R. V. Kshirsagar, "Cotton leaf disease identification using pattern recognition techniques," in Proc. of the 2015 Int. Conf. on Pervasive Computing (ICPCPune, India, pp. 1–6, 2015.
8. P. B. Padol and A. A. Yadav, "SVM classifier based grape leaf disease detection," in Proc. of the 2016 Conf. on Advances in Signal Processing (CASPPune, India, pp. 175–179, 2016.
9. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed et al., "Going deeper with convolutions," in Proc. of the 2015 IEEE Conf. on Computer Vision and Pattern Recognition (CVPRBoston, MA, USA, pp. 1–9, 2015.
10. S. S. Gaikwad and S. Singh, "Fungi classification using convolutional neural network, " *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. *12*, n o. *10*, pp. 4563–4569, 2021.
11. Y. Zhong and M. Zhao, "Research on deep learning in apple leaf disease recognition, " *Computers and Electronics in Agriculture*, vol. *168*, no. *2*, pp. 105146, 2020.
12. P. Jiang, Y. Chen, B. Liu, D. He, C. L. Jiang et al., "Real-time detection of apple leaf d iseases using deep learning approaches based on improved convolutional neural netwo rks," *IEEE Access*, vol. *7*, no. *2*, pp. 59069–59080, 201
13. M. B. Tahir, M. A. Khan, K. Javed, S. Kadry, Y. D. Zhang et al., "Recognition of appl e leaf diseases using deep learning and variances-controlled features reduction," *Micro processors and Microsystems*, vol. *7*, no. *1*, pp. 104–127, 2021.

14. Y. H. Jin, S. C. Hwan and L. D. Hyuk, “Apple leaf disease identification through regio n-of-interest-aware deep convolutional neural networks,” *Journal of Imaging Science and Technology*, vol. *64*, no. *2*, pp. 20507-1, 2020.
15. S. Baranwal, S. Khandelwal and A. Arora, “Deep learning convolutional neural netwo rk for apple leaves disease detection,” in Proc. of Int. Conf. on Sustainable Computing in Science, Technology and Management (SUSCOMJaipur-India, Amity University R ajasthan, 2020.
16. H. J. Yu and C. H. Son, “Leaf spot attention network for apple leaf disease identificati on,” in Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition Wo rkshops, China, pp. 52–53, 2020.
17. Q. Yan, B. Yang, W. Wang, B. Wang, P. Chen et al., “Apple leaf diseases recognition based on an improved convolutional neural network,” *Sensors*, vol. *12*, no. *2*, pp. 3535 –3541, 2020.
18. B. Liu, Y. Zhang, D. J. He and Y. Li, “Identification of apple leaf diseases based on de ep convolutional neural networks,” *Symmetry*, vol. *10*, no. *1*, pp. 11–16, 2018.
19. P. Bansal, R. Kumar and S. Kumar, “Disease detection in apple leaves using deep con volutional neural network,” *Agriculture*, vol. *11*, no. *7*, pp. 617–620, 2021.
20. I. Gupta, S. Gupta and S. Singh, “Breast cancer detection using deep learning and mac hine learning techniques,” *Journal of Advanced Research in Dynamical & Control Sys tems*, vol. *11*, no. *2*, pp. 1487–1498, 2019.
21. S. Singh and S. Gupta, “Apple scab and marsonina coronaria diseases detection in app le leaves using machine learning,” *International Journal of Pure and Applied Mathem atics*, vol. *118*, no. *5*, pp. 1151–1166, 20