International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6, 2025
https://theaspd.com/index.php

Environmental Monitoring Of Mango Leaf Diseases And Sustainable Treatment Using Hybrid Pso Optimization

Seema J Kampli[1], Archana B[2], Nandini G[3], Mahanthesha U[4], Kruthi P[5], Ravikiran H N[6], Divya M S[7]
[1]Professor, Department of Computer Science and Engineering ,APS college of Engineering, Somanahalli gate, Bangalore
[2]Associate Professor,Department of CSE, Vidya Vikas Institute of Engineering and Technology, Mysuru, Karanataka, India
[3]Associate Professor,Department of Information Science and Engineering,B N M Institute of Technology Benagluru.Karnataka, India.
[4]Associate Professor,Department of Artificial Intelligence and Machine Learning,B N M Institute of Technology Benagluru.Karnataka, India.
[5]Assistant Professor,Department of Artificial Intelligence and Machine Learning,B N M Institute of Technology Benagluru.Karnataka, India.
[6]Assistant Professor,Department of Electronics and Communication Engineering ,BGS Institute of Technology,Adichunchanagiri University,B G Nagara, Karnataka, India.
[7]Assistant Professor,Department of Artificial Intelligence and Machine Learning,B N M Institute of Technology Benagluru.Karnataka, India

ABSTRACT: *The categorization of the mango leaf enhances the classification process's performance by selecting the best attributes. The process becomes less complex in terms of time and algorithms when the best features are chosen. To identify the diseases in the photos of the mango leaf infection zone, KAGGLE images were utilized. Mango leaf illnesses, including bacterial black spot, twig blight, gummosis, anthracnose, and bark splitting, have been tested. From LBP features, features were retrieved. Five distinct classifiers were then used to classify the chosen features in order to evaluate their effectiveness.The performance measures were used to gauge the process's overall effectiveness. The process's primary goal is to choose the best characteristics from among the several feature types that were retrieved using various techniques. to evaluate how well various classifiers perform using the chosen features. to extract various aspects from the photos, such as texture-based and intensity-based features. Using hybrid PSO optimization techniques, this work uses the best analysis of mango leaf disease detection, classification, and therapy. The accuracy of this work in the testing datasets is 97%. Performance indicators such as accuracy, sensitivity, and specificity were used to gauge the process's effectiveness. This job was carried out with exceptional efficiency using MATLAB.*
Keywords: Mango leaf, Disease, Hybrid PSO optimization, Treatment

I.INTRODUCTION

In this research, we offer a parallel multiple classifier system and text on signatures based on raw pixel representation for the classification of emphysema in computed 1y pictures of the Mango leaf infection region. Support vector machines are used as base classifiers in the multiple classifier system, and their judgments are combined using a product rule. The suggested method is evaluated on 168 annotated regions of interest that include paraseptal emphysema, centrilobular emphysema, and normal tissue[1].
The two primary parameters of the text-on-based texture classification approach are text-on size and k value in k-means. According to our findings, merging SVMs over different text sizes is not helpful, however aggregating single judgments across a range of k values utilizing several classifier systems does improve the results when compared to single SVMs. The accuracy of 95% for the suggested system is comparable to that of a recently suggested method based on local binary patterns, which performs almost as well as other methods in the literature[2].
Using the calculated 1y images, this study presents texture-based segmentation and disease detection of the mango leaf infection zone. Gabor filtering is utilized to extract texture-based features, and the Genetic algorithm is used as an optimal initialization of the clusters paired with feature selection approaches as Information Gain, Principal Component Analysis, and correlation-based feature selection. Using fuzzy C means clustering and watershed segmentation, the feature outputs are integrated. The pictures are identified using both shape-based and statistical criteria[3].

To categorize the datasets, the Naive Bayes classifier is used for training and testing, taking into account the four classes of the Mango Leaf Infection Region Diseases dataset. The findings of this study demonstrate that the correlation-based feature selection method for the four dataset classes has an accuracy of above 90%. Gathering several datasets on mango leaf illnesses, including Anthracnose, Bacterial Black Spot, Twig Blight, Gummosis, and Bark Splitting, from digital cameras is the initial step in this project[4].

Figure 1: Mango leaf infection datasets

Diseases caused by mango leaf infection are the world's top cause of mortality and disability. The outcome of the radiotherapy and the radiologist's diagnosis of the chest depend on the drug dosages administered and how they impact the surrounding normal tissues. The first significant modality of illness assessment is the chest. The picture and disease symptoms will provide a thorough evaluation of the diseases that affect the mango leaf infection region. Smoking, drug inhalation, smoke inhalation, and allergic substance exposure are the main causes of diseases in the mango leaf infection zone[5].

Diseases in the mango leaf infection region are typically diagnosed by their symptoms, and they may be cured with consistent antibiotic use. In the event that medications are ineffective, the calculated 1y pictures help determine the extent of the infections affecting the mango leaf infection zone. Mango leaf infection region infections can be caused by a variety of diseases, including inflammatory diseases, chronic obstructive pulmonary disease (COPD), pleural effusion, emphysema, chronic bronchitis, and mango leaf infection region carcinoma[6].

The large cell and small cell carcinomas of the mango leaf infection region are the datasets of the diseases that are taken into consideration in this study. Mango leaf infection region cancer, also known as mango leaf infection region carcinoma, is the most prevalent cause of cancer death for men globally and the most common major cancer to be identified. Cigarette smoke's effects are mostly to blame for this. To provide uniformity in patient care and to serve as the foundation for biological and epidemiological research, an international categorization system for mango leaf infections is essential[7].

Pathologists have attempted to decrease the number of unclassifiable lesions while adhering to the principles of clinical significance, simplicity, and reproducibility in the development of this classification. Although immunological histochemistry and electron microscopy results are provided where required, the majority of this classification is based on the histological features of mango leaf infections observed in surgical or needle biopsies. According to the methods employed in this work, the photos are pre-processed to eliminate noise, and contrast enhancement is carried out to produce the improved images. The Gabor filter is utilized in texture analysis, and feature extraction is often employed as a preprocessing step to machine learning[8].

rincipal Component Analysis, correlation-based feature selection, information gain, and genetic algorithm optimization are examples of feature selection techniques. Watershed segmentation is used to aggregate the feature outputs, and fuzzy C means clustering is used to mix data from two or more clusters. The pictures are classified using the Naive Bayes classifier, and the outcomes are displayed along with performance metrics. The diagnosis and treatment of cancer in the mango leaf infection zone depend heavily on the early detection of lung nodules. This work uses hybrid characteristics to propose a new classification method for lung nodules from KAGGLE images. Four distinct approaches are presented for the suggested system. Several classifiers are used to assess the overall detection performance. Standard metrics are used to compare the results to similar methods in the literature. With the hybrid characteristics, the suggested method achieves 90.7% classification accuracy (89.6% sensitivity and 87.5% specificity)[9].

An increasing number of studies are characterizing patterns of anatomical differences that can be identified from neuroimaging data using machine learning techniques. Because picture data is high-dimensional, it is frequently feared that feature selection is necessary to achieve the best accuracy. Some earlier research, which mostly used fixed sample sizes, demonstrate higher prediction accuracies with feature selection than others. We compared four popular feature selection techniques in this study. 1) Regions of interest (ROIs) that have been pre-selected using past information. 2) Filtering using the univariate t-test. 3)[10].

Recursive feature elimination (RFE), and 4) ROI-constrained t-test filtering. A statistical comparison was made of the prediction accuracy attained by various sample sizes, both with and without feature selection. To illustrate the effect, we fed a linear support vector machine classifier using grey matter segregated from the T1-weighted anatomical scans gathered by the Alzheimer's disease Neuroimaging Initiative (ADNI)[11, 12].

II. LITERATURE REVIEWS

The authors of the publication "Deep learning for Image-Based Plant detection" [1], Prasanna Mohanty et al., have suggested a method for identifying plant diseases through convolutional neural network training. The CNN model has been trained to recognize 14 different species of plants as healthy or ill. On test set data, the model's accuracy was 99.35%. The model's accuracy of 31.4% when applied to photos sourced from reliable websites is superior to that of a basic random selection model; nevertheless, a more varied set of training data can help improve the accuracy. Additionally, different model or neural network training changes might produce better accuracy, opening the door for universal access to plant disease diagnosis. In the study "Detection and Classification of Leaf Disease using Artificial Neural Network," Malvika Ranjan et al. suggested a method for identifying plant illnesses by using an image of the afflicted leaf[13].

To differentiate between healthy samples and diseased plants, an Artificial Neural Network (ANN) is trained by appropriately selecting feature values. The accuracy of the ANN model is 80%. The four primary steps in the disease identification procedure are as follows, per the publication "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features" [3] by S. Arivazhagan: The input RGB image is first given a color transformation structure. Next, the green pixels are identified and removed using a predetermined threshold value. This is followed by the segmentation process, and texture statistics are calculated to generate useful segments[14].

Finally, a classifier is used to the retrieved features in order to categorize the illness. In the publication "Applying image processing technique to detect plant diseases," Kulkarni et al. describe a methodology that uses artificial neural networks (ANN) and several image processing techniques to detect plant illnesses reliably and early. With a recognition rate of up to 91%, the suggested method produces better results because it is based on an ANN classifier for classification and a Gabor filter for feature extraction. Emaneul Cortes' study "Plant disease detection using CNN and GAN" [15] suggests a method for identifying plant diseases through the use of generative adversarial networks.

In order to guarantee appropriate feature extraction and output mapping, background segmentation is utilized. Gans may be a promising tool for plant disease classification, however background-based segmentation did not increase accuracy. Jyotsna Bankar et al. suggested using the Inception v3 model to categorize animals of various types in their paper "Convolutional Neural Network based Inception v3 Model for Animal Classification" [16]. Both object classification and categorization are possible with Inception v3, which makes it useful for a variety of image classifiers.

III. EXISTING SYSTEM

In order to identify the diseases in the photos of mango leaves, classification techniques were used to classify the images. Using rule-based classifiers, which group pixels with similar outcomes for the rules applied into a group, the faults were identified. Depending on the applications the process is utilized for, the classifier's rules vary. Classifiers that use linear discriminant analysis (LDA) determine the regions' flaws by comparing the features in the pictures[17].

Based on similar patterns in the retrieved features, the artificial neural networks (ANN) classifiers categorize the photos. Patterns in the data were found to belong to comparable groups during the training procedure. Bayesian classifiers were probability-based classifiers that determined the likelihood that features would be extracted and then classed the images according to the probability that was determined[18].

Concept of LDA

One popular method for dimension reduction and feature extraction is Linear Discriminant Analysis (LDA). It has been extensively employed in numerous high-dimensional data applications, including picture retrieval and face recognition. The so-called singularity problem, which occurs when all scatter matrices are singular, is an inherent drawback of classical LDA. Applying an interim dimension reduction stage utilizing Principal Component Analysis (PCA) prior to LDA is a well-known method for addressing the singularity issue[19].

Face recognition makes extensive use of the PCA+LDA method. However, because an eigen-decomposition involving the scatter matrices is required, PCA+LDA has significant temporal and spatial overhead.

Analysis of Process

Chest radiography and computed 1y (CT) are frequently used to identify solitary pulmonary nodules (SPNs). In order to further assess the nodules, biopsies are frequently conducted. The expense and morbidity of invasive tissue sample may be avoided with a precise, noninvasive diagnostic procedure. In a prospective, multicenter study, we assessed the capacity of fluorine-18 deoxy glucose positron emission tomography (FDG-PET) to distinguish between benign and malignant lung nodules.

FDG-PET was used to assess 89 individuals with recently discovered indeterminate SPNs on chest radiography and KAGGLE. Both a visual scoring approach and the calculation of standardized uptake values (SUVs), which serve as an indicator of FDG buildup, were used to semi-quantitatively interpret PET data. The pathology and PET data were contrasted. Of the SPNs, 29 were benign and 60 were malignant. PET's overall sensitivity and specificity for identifying malignant nodules using SUV data were 92% and 90%, respectively. A slightly greater, but not statistically significant, sensitivity of 98% and a lower specificity of 69% were obtained using visual analysis. The sensitivity and specificity of SUV and visal analysis were 80% and 95% and 100% and 74%, respectively, for SPNs < or = 1.5 cm (34 of 89)[20].

Solitary pulmonary nodules can only be reliably distinguished as benign or malignant based on two radiological features. It is obvious from intuition that additional clinical and radiographic evidence ought to play a significant role in drawing this distinction. It is challenging to subjectively include these additional features when determining whether a nodule is benign or cancerous. The Bayes theorem[21] can be used to quantify the likelihood of malignancy of a particular nodule by combining likelihood ratios, which show the degree of malignancy or benignity reflected by a test result or clinical finding.

Likelihood ratios for four clinical and six radiographic features linked to solitary pulmonary nodules were obtained from a review of the literature. Radiographic features were the most significant of the 19 benign and 15 malignant findings that were found. The two most crucial radiographic features for malignant nodules were a diameter of more than 3 cm and the thickness of the cavity wall spicular edge. The two most crucial radiographic features for benign nodules were a benign calcification pattern and a benign development rate.

IV. PROPOSED SYSTEM

In order to categorize various textural patterns in the mango leaf infection zone, we propose to employ local binary patterns (LBP) as features in a classification framework. The joint LBP and intensity histogram is used to include image intensity, and the k closest neighbor classifier is used for classification, utilizing histogram similarity as a distance metric[22]. A filter bank based on Gaussian derivatives is compared to a collection of 168 locations of interest that include both normal tissue and various emphysema patterns in order to assess the suggested strategy shown in figure 2.

With a classification accuracy of 95.2%, the joint LBP and intensity histogram outperforms the popular method of employing the filter response histograms' moments as features and performs somewhat better than the entire filter response histograms. The results of the classification are superior to some of the earlier findings in the literature[23].

Advantages: The study of the various classifier types is aided by the classifier comparison.
• The best features from the dataset are chosen using an efficient feature selection procedure.
• The PSO is responsible for the feature selection process's effectiveness.
• The suggested feature extraction method is more effective when applying the features using a KNN classifier, as demonstrated by the performance metrics employed.

Disadvantages:
• The various classifiers were used to compare how the characteristics were classified. There was no comparison of the feature extraction procedure.
• The current approaches did not use the estimation of optimal features.
• The existing approaches made greater use of the textural aspects. To extract the best features from the photos, the statistical parameters and intensity-based features were also required in the case of mango leaf infection.

V. METHODOLOGY

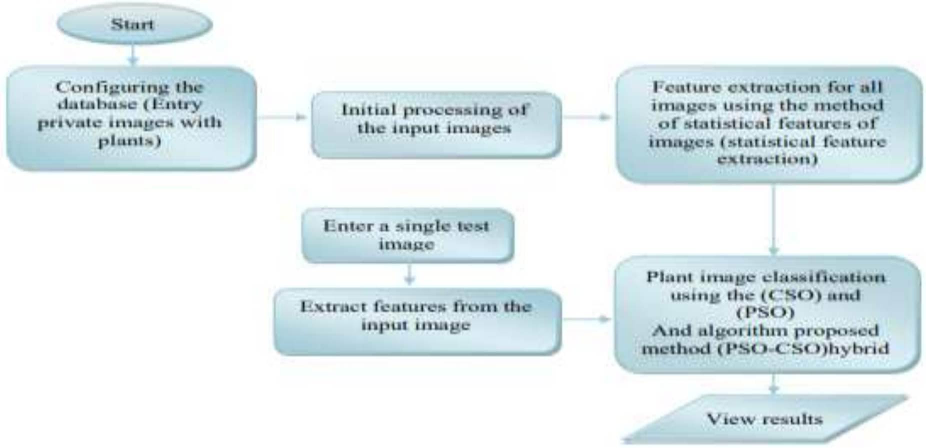

Figure 2: Architecture of Mango leaf infection region Imaging classification and treatment analysis
The Figure 2 illustrates how the suggested paradigm operates in detail.
Step 1: The infected mango leaf, also known as the input image, is tested.
Step 2: The input image is scaled to 256 x 256 and preprocessed using a Gaussian filter.
Step 3: Infected features are extracted during the extraction procedure following preprocessing.
Step 4: PSO Optimization and distance measures are used to classify the chosen features.
Step 5: Following estimation, the performance metrics are computed and presented in terms of accuracy, sensitivity, and specificity.

List of algorithms compared:
This study suggests a method for identifying Common Imaging Signs of Lesions (CISLs) in KAGGLE images of the mango leaf infection zone. We express regions of interest (ROIs) in Mango leaf infection region KAGGLE images by combining the bag-of-visual-words based on the Histograms of Oriented Gradients (HOG) and the Local Binary Pattern (LBP). The category of the imaging sign included in each ROI is then identified using the Max-Min posterior Pseudo-probabilities (MMP) learning technique. Using a collection of 696 ROIs taken from actual Mango leaf infection region KAGGLE pictures, we carried out the 5-fold cross validation studies.
The average sensitivity, specificity, and accuracy of the suggested method were 91.8%, 98.5%, and 98%, respectively. Additionally, the MMP outperformed the Support Vector Machines (SVMs)[24], and the HOG-LBP features outperformed both solo HOG or LBP and the hybrid of LBP and intensity histograms. These experimental findings support the efficacy of our strategy.

Flow diagram of Mango leaf infection region Imaging classification and treatment analysis shown in figure 3.

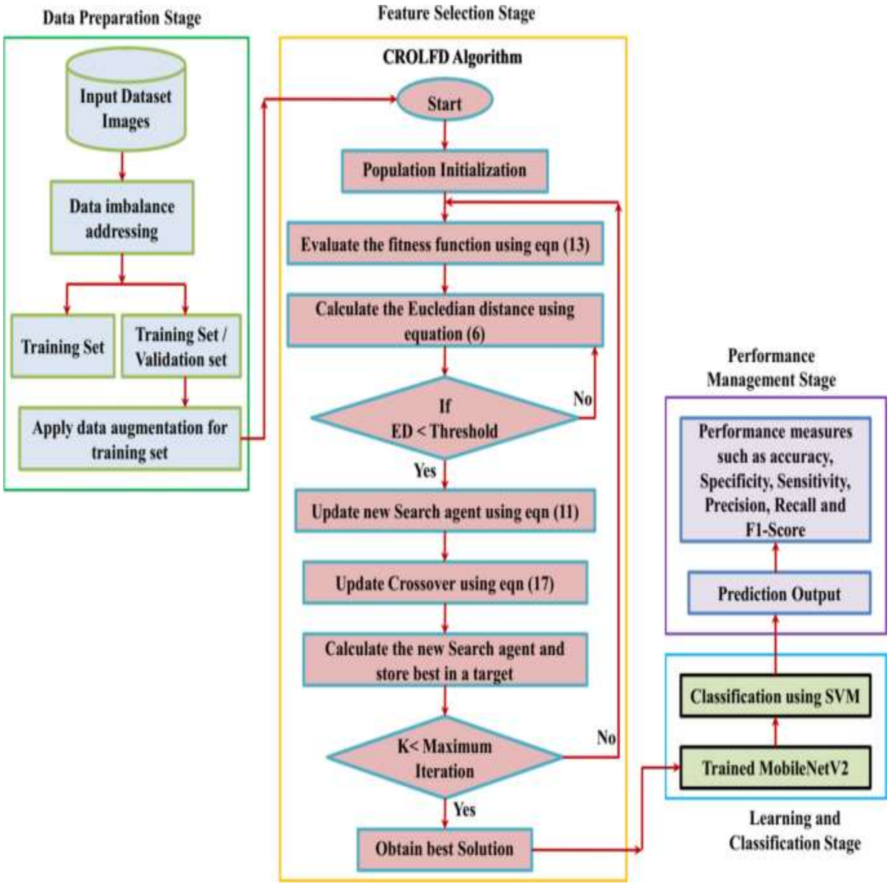

Figure 3: Flow diagram of Mango leaf infection region Imaging classification and treatment analysis

VI. RESULTS AND DISCUSSIONS

The input and output parameters of this work, which uses LBP and hybrid PSO optimization approaches to detect mango leaf illness and offer treatment options, are demonstrated in the screenshots that follow, ranging from Figure 3 to Figure 10.

Particle Swarm Optimization: In order to replicate the social behavior of birds, two scientists (Eberhardt and Kennedy) developed the PSO algorithm. It is regarded as one of the unsupervised algorithms, and it relies on the swarm of particles to find and arrive at the answer throughout the search space. A suggested solution to the optimization problem is represented by each of these particles. [25,26,27].

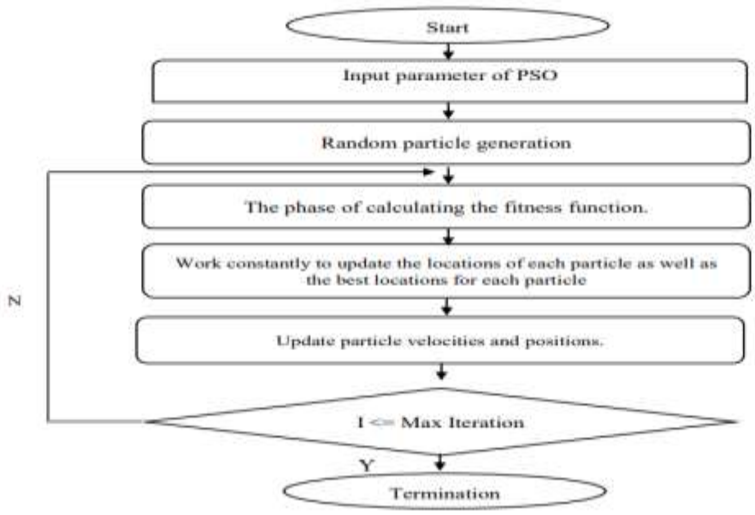

Figure 4: Diagram of Particle Swarm Optimization

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6, 2025
https://theaspd.com/index.php

The proposed hybrid method (PSO-CSO) is an algorithm that was created by combining and hybridizing the (PSO) and (CSO) algorithms. Its hybridization process relies on the way the (CSO) algorithm operates in every step, but it modifies the equations for updating and determining the positions of the cocks in the algorithm.

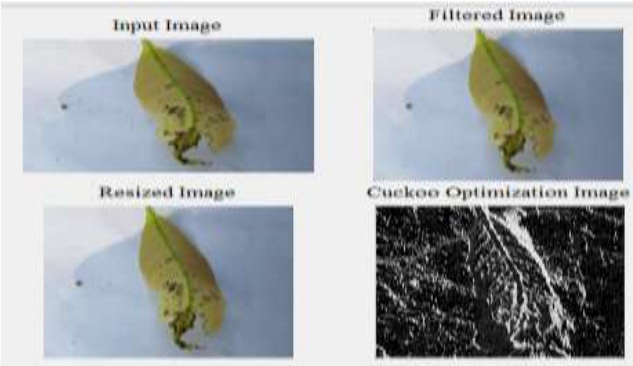

Figure 3: Dataset loading, filtering, resizing and LBP feature of the implementation

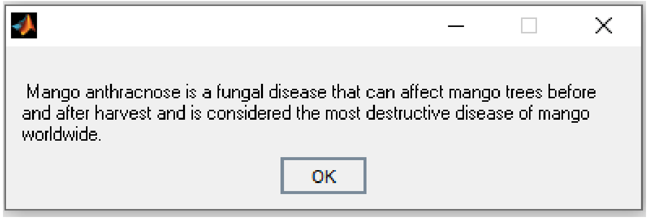

Figure 4: Result obtained as Mango leaf anthracnose image and its details explained by the ML module

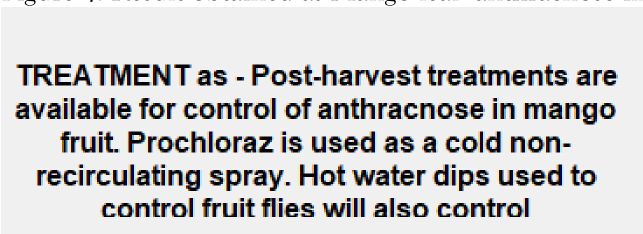

Figure 5: Result obtained as treatment suggestion Mango leaf anthracnose image and its details explained by the ML module

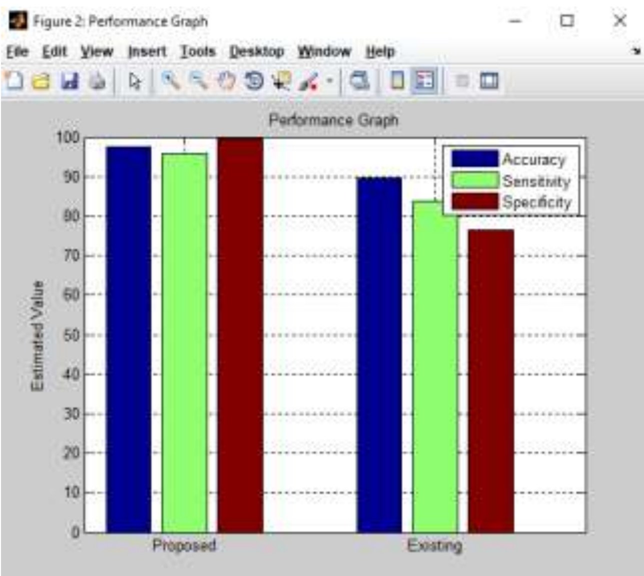

Figure 6: Performance graph of existing and proposed work

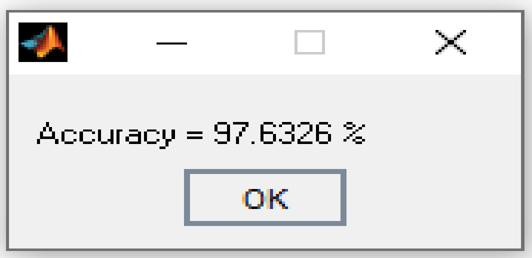

Figure 7: Accuracy of the Mango leaf disease detection and its treatment analysis

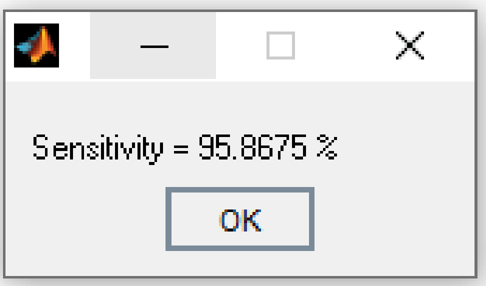

Figure 8: Sensitivity of the Mango leaf disease detection and its treatment analysis

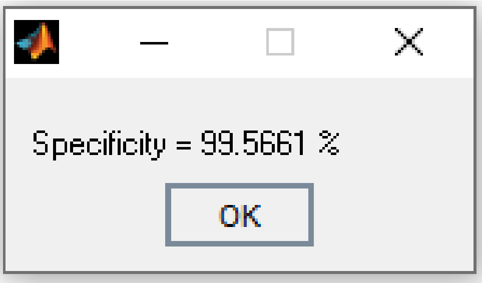

Figure 9: Specificity of the Mango leaf disease detection and its treatment analysis

Table.1.Results of the testing process for the first test images of eight plants using algorithms PSO, CSO, and Proposed hybrid method (PSO -CSO).

Methods	No of images taken for testing	Classification rate
PSO	225	%94.2
CSO	225	%92.8
Proposed hybrid **method (PSO - CSO)**	225	%96.9

CONCLUSION

Images of the infected areas of mango leaves were used as the input. Images of mango leaf infection regions with nine distinct disease types make up the dataset. Because the other regions might include some undesired information, the ROI was chosen from the photos of the mango leaf infection region. Four distinct feature categories were retrieved in order to do so. A genetic algorithm using the Fisher criterion is used to choose the best features from the extracted features. The KNN classifier was then used to classify the chosen characteristics. PSO yields optimization solutions that are more precise. The halting condition can be more precisely defined and convergence can be accomplished more successfully with swarm-based optimization techniques.

REFERENCES

[1] Tejaswini R. Murgod, S. Meenakshi Sundaram, U. Mahanthesha, Vaidyanathan Murugesan, "A Survey of Digital Twin for Industry 4.0: Benefits, Challenges and Opportunities", Springer Nature Singapore Pte Ltd 2023, https://doi.org/10.1007/s42979-023-02363-2

[2] Debnath, S., Preetham, A., Vuppu, S., & Kumar, S. N. P. (2023). Optimal weighted GAN and U-Net based segmentation for phenotypic trait estimation of crops using Taylor Coot algorithm. Applied Soft Computing, 144, 110396.

[3] Nagarathna, C. R., & Kusuma, M. M. (2023). Early detection of Alzheimer's Disease using MRI images and deep learning techniques. Alzheimer's & Dementia, 19, e062076.

[4] Huliyappa, H. (2024). Ensemble Stacking Method of Classifying the Stages of Alzheimer's Disease by using MRI Dataset. International Journal of Artificial Intelligence, 11(2), 62-69.
[5] Mahanthesha U, Divyashree N, Kanchana R, Deepika KC, Naveen N , Prathibha G, "Smarter Help and Seamless Experience of Automated User Responsive Assistant (AURA) Robot using NLP", Tuijin Jishu/Journal of Propulsion Technology ISSN: 1001-4055 Vol. 46 No. 2
(2025), https://www.propulsiontechjournal.com/index.php/journal/article/view/9581
[6] Nagarathna C R, Archana B, Anjaneya L.H, Mahanthesha U, Nandini G, Babu Kumar S, "Classification of Alzheimer's Disease Using Deep Learning based Edge Detection and Fuzzy Neural Network", Tuijin Jishu/Journal of Propulsion Technology ISSN: 1001-4055Vol. 45No.
2(2024), https://propulsiontechjournal.com/index.php/journal/article/view/6787/4438 .
[7] Nagarathna, C. R., Bhagya, K. G., Devaraju, H. B., Somashekara, A. S., & Kishore, H. N. (2025). Machine Learning Techniques for EEG-Based Alzheimer's Disease Classification. Mathematical Modelling of Engineering Problems, 12(3).
[8] CR Jr, N., & MM Sr, K. (2022). Ensemble approach for early detection and classification of stages of Alzheimer's disease. Alzheimer's & Dementia, 18, e059124.
[9] Chandana, S., Nagarathna, C. R., Amrutha, A., & Jayasri, A. (2024, January). Detection of image forgery using error level analysis. In 2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE) (pp. 1-5). IEEE.
[10] Bhavyashree, H. L., Nagarathna, C. R., Preetham, A., & Priyanka, R. (2019, March). Modified cluster based certificate blocking of misbehaving node in MANETS. In 2019 1st international conference on advanced technologies in intelligent control, environment, computing & communication engineering (ICATIECE) (pp. 155-161). IEEE.
[11] Nagarathna, C. R., & Chinnaswamy, C. N. (2014). The technique to detect and avoid the denial of service attacks in wireless sensor networks. International Journal of Research in Engineering and Technology (IJRET), 3(05)..
[12] Mahanthesha U, Vinay Kumar, Suzane Fernandes, Shri Ranjani S M & Shrividya K P "Inverse Recipe Generation and Food Quality Detection", 10.37896/YMER23.05/45, YMER || ISSN: 0044-0477, https://ymerdigital.com/archives/?cpage=3&issId=%202305 , page no 526-531, May 2024,
[13] Mahanthesha U, Tejaswini R. M, Nagarathna C R, Y Tejal Ravikumar, presented a research article "Face Recognition using MTCNN, Inception - Resnet with Ensemble Approach", in 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE) and published in IEEE Xplore DOI: 10.1109/IITCEE64140.2025.10915271 , Date Added to IEEE Xplore: 14 March 2025.
[14] Karthik N G, Kaushal A N , Prajwal Harish, Jagruthi H, Mahanthesha U, presented a research article "Automated Parsing and Comparative Analysis of ASN.1 Structures in 3GPP Standards", in 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE) and published in IEEE Xplore DOI: 10.1109/IITCEE64140.2025.10915300 , Date Added to IEEE Xplore: 14 March 2025.
[15] Dr. Raghavendra C K, Dr. Mahanthesha U, Prashanth J, "Cascading based Hybrid Recommendation Model" IEEE Xplore 2024, Pages: 181-188,
DOI: 10.1109/ICMCSI61536.2024.00033 https://www.computer.org/csdl/proceedingsarticle/icmcsi/2024/952300a181/1W3wG6JuG2Y, 2024
[16] Preetham, A., Vyas, S., Kumar, M., & Kumar, S. N. P. (2024). Optimized convolutional neural network for land cover classification via improved lion algorithm. Transactions in GIS, 28(4), 769-789.
[17] Preetham, A., & Battu, V. V. (2023). Soil Moisture Retrieval Using Sail Squirrel Search Optimization-based Deep Convolutional Neural Network with Sentinel-1 Images. International Journal of Image and Graphics, 23(05), 2350048.
[18] Nagamalla, V., Kumar, B. M., Janu, N., Preetham, A., Parambil Gangadharan, S. M., Alqahtani, M. A., & Ratna, R. (2022). Detection of adulteration in food using recurrent neural network with internet of things. Journal of Food Quality, 2022(1), 6163649.
[19] Preetham, A., & Almas, M. (2023). Alzheimer's Classification from EGG Signals Employing Machine Learning Algorithms. Journal of Electronics and Informatics, 5(4), 386-404.
[20] Nagarathna, C. R., & Mohanchandra, K. (2023). An overview of early detection of Alzheimer's disease. International Journal of Medical Engineering and Informatics, 15(5), 442-457.
[21] Rangegowda, N. C., Mohanchandra, K., Preetham, A., Almas, M., & Huliyappa, H. (2023). A Multi-Layer Perceptron Network-Based Model for Classifying Stages of Alzheimer's Disease Using Clinical Data. Revue d'Intelligence Artificielle, 37(3), 601.
[22]Enhancing Cyber Security through Machine Learning-Based Anomaly Detection in IoT Networks" Dr. Shreyas,, Dr. Sudhakar K, Dr. I. Bhuvaneshwarri,Thamaraiselvan B, Lakshmi.M, Dr Pooja Nayak S International Journal on Recent and Innovation Trends in Computing(Q4 Journal) and Communication ISSN: 2321-8169 Volume: 11 Issue: 10
[23]A Framework for Brain Tumor Image Analysis using Convolution with RELU" Pallavi Hallappanavar Basavaraja, Nandeeswar Sampigehalli Basavaraju, Pooja Nayak S, Anusha Preetham, Ramya R. S., Shravya S. International Journal Of Intelligent Systems And Applications In Engineering (Q3 Journal) ISSN:2147
[24]Pooja Nayak S, DR S G Hiremath, Dr Arun Biradar, "Classifying Emotional traits from Speech file using Machine Learning", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2, December 2019
[25]Pooja Nayak S, DR S G Hiremath, Dr Arun Biradar, Speech Classification using Logical ART Deep Mechanism of Machine Learning, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2
[26] C R, N. . (2025). Intelligent aerial surveillance for safer railways using machine learning. International Journal of Innovative Research and Scientific Studies, 8(5), 1160–1166. https://doi.org/10.53894/ijirss.v8i5.9077