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An Intelligent Grape Leaf Disease Identification Model Using WOA-Optimized XG- Boost Classifier

R. Sahila Devi[1*], A. T. R. Krishna Priya[2], P. Karputha Pandi[3]

[1]Department of Computer Science and Engineering, Assistant Professor, Rohini College of Engineering and Technology, Kanyakumari, India.
[2] Department of Computer Science and Engineering, PG Scholar, Rohini College of Engineering and Technology, Kanyakumari, Tamilnadu, India.
[3]Department of Electrical and Electronics Engineering, Assistant professor, Erode Senguthar Engineering College, Perundurai.
***Corresponding Author E-mail: r.sahiladevi@gmail.com**

ABSTRACT: Grape Leaf Disease (GLD) identification have become a significant agricultural issue with an alarming rise in recent years, necessitating effective prediction algorithms. In this paper, Whale Optimization Algorithm based XG Boost classifier is proposed for prediction of GLD such as Black Rot, ESCA, healthy, Leaf blight. Initially, image resizing is applied to the grapevine disease dataset to resize the image, noise reduction to reduce the unwanted noise and improve the clarity of unclear image using Contrast-Limited Adaptive Histogram Equalization (CLAHE). Next, the processed image is given to the Otsu's segmentation, to calculate the threshold value. After that grape leaf image is featured using Local Binary Patten (LBP) for analysing local texture structure. Finally, a WOA optimized XG Boosting framework is processed to enhance the classification of GLD for analysis. Using python software proposed framework have accuracy of 92.41% is accomplished when compared to other techniques.

Keywords: Whale Optimization, Algorithm (WOA), XG Boosting Classifier, Image resizing, Noise reduction, CLAHE, Otsu's Segmentation, Local Binary Pattern, GLD.

1. Introduction

Grapes are one of the most widely consumed fruitlets worldwide and main ingredient used to make wine, their yield and quality have significant economic importance [1]. Conversely, grape leaves are vulnerable to a number of viruses that are mostly by bacteria, viruses, and fungi and are impacted by the climate and weather. Grape quality and yield are impacted when sick leaves are not adequately managed since the disease spread to the entire plant. It is difficult to identify the disease quickly when the leaves are sick [2]. Therefore, early prevention and treatment of grape diseases greatly depend on the quick and precise detection of these conditions [3]. A thoughtful step in reducing losses by plant diseases is early and precise diagnosis. An inaccurate diagnosis results in poor management selections, such as choosing the wrong chemical application, which could cause additional health problems and lower yield [4-5]. Moreover, these diseases, which include leaf blight, black measles, and black rot, show various physical characters on grape leaves, such as variations in the form, color, and shape of various leaf segments that make them challenging to identify [6]. There are many research findings in the arena of plant disease identification in adding to grape disease identification using the machine learning, deep learning and optimization techniques [7]. Figure 1shows the GLD.

Figure 1: *Basic GLD image*

To detect the grape leaf disease Adaptive Snake Model (ASM) for segmentation is used as region identification. ASM have faster segmentation using common segmentation and higher accuracy through absolute segmentation. Decreasing its ability to adjust the objects with distinguished shape alterations outside of the training data range [8].For this reason classification technique is needed to classify the GLD. The classification performance of the Fuzzy C-means Clustering is to detect and classify the grape leaf lesion. Here, the distinct feature of grape leaf lesions on digital image is to treat then manages the disease's symptoms earlier. It is computationally expensive in contrast to other clustering techniques [9]. Moreover, using Multi-class Support Vector Machine (SVM) classifiers the grape leaf disease is diagnosed and classified successfully. Then K-means clustering is used to automatically differentiate the leaf's disease-symptomatic portion from its healthy sections. It is difficult to handle unbalanced data and inadequate performance when dealing with noisy data [10].

For grape leaf disease identification several deep learning is used as following. To detect then categorize grape leaf disease based on RGB leaf images with higher accuracy a Deep Convolutional Neural Network (DCNN) model is used. DCNNs have high processing difficulties, lacking a portion of labeled data [11]. However, to enhance the classification accuracy Convolutional Neural Network based (CNN) model is combined with Improvised K-Nearest Neighbor (IKNN). The IKNN preciously detects the grape leaf disease. Poor speed, problems with memory and storage for large datasets [12]. Using a Grape Leaf Disease Detection Technique (GLDDT) by Faster Region based Convolutional Neural Network (FRCNN) it automatically diagnosis the grape leaf disease. Here using Faster Region based CNN (FRCNN) the normal objects are detected successfully. FRCNN produces less accurate localizations because it requires a fixed-size input [13].

Furthermore, a Convolutional Capsule Networks is used to recognize GLD. This network efficiently expresses spatial information of features by using a collection of neurons as capsules. Convolutional layers are added before the primary caps layer, which indirectly reduces the number of capsules and advances the process. Network algorithm design sensitivity and a dearth of well-developed implementations [14]. Moreover, using VGG-19 CNN model the grape leaf disease detected with high performances. It correctly identifying and classifying different grape leaf diseases, eventually paving the way to more efficient agricultural disease control. It takes more time to train its parameters because it is a large network [15]. To overcome these limitations the developed work introduces WOA-XGBoost.

2. Related work

Bajait *et al* [16] (2024) have proposed a Deep Neuro-Fuzzy network (DNFN) with Sine Cosine Butterfly Optimization (SCBO) in mixing Monarch Butterfly Optimization (MBO) besides Sine Cosine Algorithm (SCA) to classify the grape leaf disease. DNFN –SCBO effectively identify the GLD. Low accuracy in complex issues, especially when working with high-dimensional search spaces.

Alsubai *et al* [17] (2023) have proposed a Hybrid Deep Learning by Improved Salp Swarm Optimization-based Multi-class Grape Disease Classification (HDLISSA-MGDC) model to classify the GLD. The classification of GLD categorized effectively using HDLISSA-MGDC model. It takes more time to process the classification.

Prabu *et al* [18] (2023) have proposed Boosted Support Vector Machine-based Arithmetic Optimization Algorithm (BSVM-AOA) for precise detection of plant leaf disease. The BSVM-AOA model is reliable enough to accurately and efficiently identify and classify leaf disease. When identifying leaf diseases, several issues are increased, such is poor identification speed, high computation costs, and inadequate precision.

Kaur *et al* [19] (2024) have proposed a K- Means Clustering optimized by Grey Wolf Optimization (GWO) for the accurate prediction of GLD. To segment the GLD by K-Means Clustering optimized by GWO. The K- Means clustering optimized by GWO is a metaheuristic technique used to detect grape leaf disease with high performance. Slow convergence and local minima susceptibility are two drawbacks of GWO.

Cai *et al* [20] (2023) have proposed a Siamese Network (Siamese DWOAM-DRNet) constructed using the Double-factor Weight Optimization Attention Mechanism (DWOAM) and the Diverse-branch Residual Module (DRM) on the way to classify GLD. Siamese DWOAM-DRNet is used to detect GLD with high performance. Greater computational difficulties, over fitting risk are some of the drawback of Siamese DWOAM-DRNet.

The contribution of this study is summarized as follows:

- Introduces noise reduction, image resizing and CLAHE to resize, remove unwanted noise and enhance the contrast of the image quality for grape leaf disease.
- Better segmentation and feature selection using Otsu's segmentation and Local Binary Pattern for classification
- Develops a Whale Optimization Algorithm (WOA) optimized XGBoost classifier to enhance grape leaf disease accuracy and efficiency.
- Validates the proposed model using metrics like accuracy, precision, recall, F1-score, and AUC, demonstrating significant improvement over existing methods.

3. Proposed work

The proposed block diagram in figure 2 for GLD classification by Machine Learning technique is applied to grapevine disease datasets. Initially the input GLD image is resized. Then unwanted noise is reduced using noise reduction and improves the clarity of unclear image using CLAHE technique. Then the processed grape leaf image is given as input to Otsu's segmentation here it calculate the threshold value to segment the grape leaf disease.

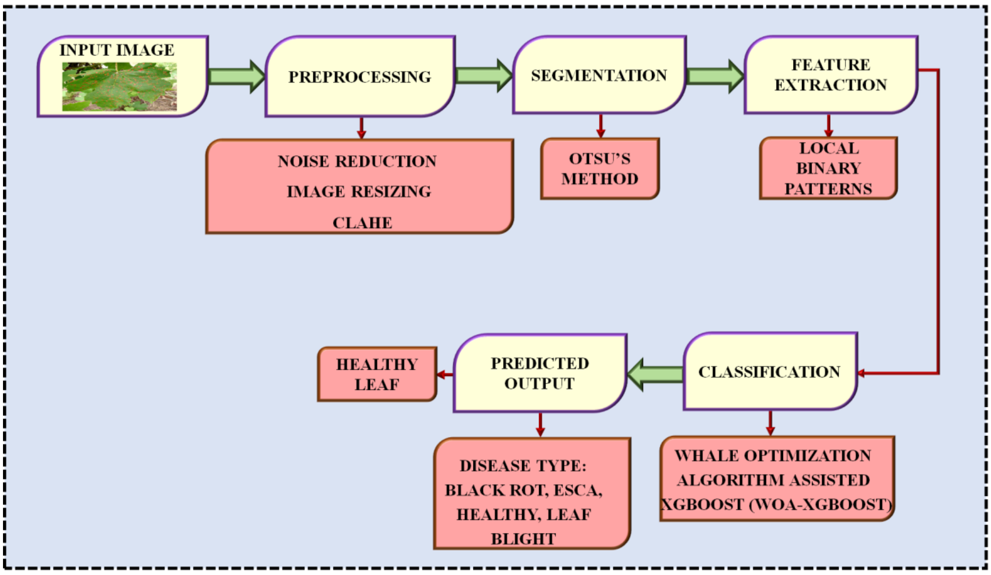

Figure 2: *Block diagram of proposed WOA-XGboost*

Next, the segmented grape leaf image is given as input to feature extraction by Local Binary Pattern. Here the local texture structure is extracted. Finally, model training is optimized using the extracted image for classification. In classification stage, a WAO-XG Boosting is utilized to increase the accuracy and efficiency. To improve model accuracy, faster convergence of grape leaf illness the optimization technique is used.

3.1 Pre-processing for grape leaf disease:

In the grape leaf disease identification pre-processing have three techniques image resizing, noise reduction and contrast enhancement.

3.1.1 Image resizing

The purpose of the preprocessing stage is to enhance the grape leaf disease image by eliminating unwanted distortions and background noise. It improves the features of images for analysis and processing. The RGB-formatted images are resized to their standard sizes. The HSV format is then applied to these RGB images that have been resized. Resizing the image to a standard matrix improves computation accuracy and performance.

3.1.2 Noise reduction

To improve the accuracy of disease symptoms and the precision of disease identification, noise reduction is used. And to eliminate unwanted disturbances or irregularities from a captured grape leaf image wiener filter is used as noise reduction. This is usually done during the pre-processing stage. A Wiener filter is a statistical method for restoring images and eliminating noise which is express as

$$\varphi(k,l) = \frac{H^*(k,l)}{(|H(k,l)|)^2 + \frac{\sigma_v^2}{P_s(k,l)}} \tag{1}$$

3.1.3 CLAHE

Contrast-Limited Adaptive Histogram Equalization (CLAHE) is by defining a maximum contrast also known as a clip level. The background extraction method must be flexible enough to adjust to the unique characteristics of each image in order to recognize it. CLAHE is used to create histograms of pixel values and the values of the surrounding regions. CLAHE will limit the maximum contrast adjustment to the local histogram height and consequently, maximize contrast enhancement factor. As a result of this, the final image looks cleaner. The resulting images show a clear graininess, even though this technique allows one to distinguish between the motion and the noise. Following to this the pre-processed image is given to the segmentation.

3.2 Otsu’s segmentation

One general method in the grape leaf disease segmentation area of image processing is Otsu's segmentation. Using the image thresholds, the Otsu’s segmentation automatically clusters the GLD images, by reducing the grayscale image to a binary image. Grape leaf shows the change in color area that is diseased. Therefore, the greenness of the grape leaf identifies the affected area. Next, the images' R, G, and B components are taken out. The threshold is determined using Otsu's technique. The green pixels are then hidden and removed if the pixel intensities fall below the determined threshold.

The Otsu computation described here is as follows:

- It will separate the pixels into two groups according to the limit valve it obtained from Otsu's method.
- Find the mean of each group at that point.
- Determine the mean difference and square it.
- The number of pixels in single cluster is multiplied by the number of clusters in the other cluster.

This method makes the assumption that images have two pixel classes which are frontal area pixels and background pixels that includes a bimodal histogram. The class means $\mu_0(t), \mu_1(t)$ *and* μ_T are

$$\mu_0(t) = \frac{\sum_{i=0}^{t-1} ip(i)}{\omega_0(t)} \quad (2)$$

$$\mu_1 \quad (t) = \frac{\sum_{i=t}^{L-1} ip(i)}{\omega_1(t)} \quad (3)$$

$$_T = \sum_{i=0}^{L-1} ip(i) \quad (4)$$

It is easily verified by the following equation

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T \quad (5)$$

$$\omega_0 + \omega_1 = 1 \quad (6)$$

Iterative calculations of the class means and probabilities are possible. Following by segmentation the grape leaf disease is given to the feature extraction.

3.3 Feature extraction using Local Binary Pattern

Local Binary Pattern (LBP) for grape leaf disease is an effective and consistent feature for analyzing local texture structures. Texture formation at the pixel level, is defined on the basis of local patterns. LBP describes complex structures in a grape leaf image using the several simple primitives. LBP takes into account both the placement rule property of structural analysis and texture primitives. One of the most effective texture descriptors is assumed to be local binary patterns. A 3x3 pixel window is the definition of the traditional LBP operator in figure 3.

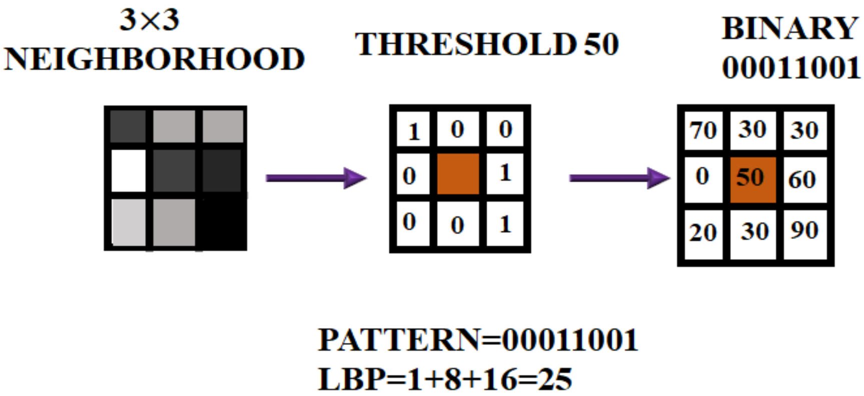

Figure 3: *Local Binary Pattern*

If the value of the neighboring pixel is less than the threshold value, the pixel value is labeled 0. The center pixel of this window serves as a threshold. It is labeled 1 otherwise.

$$LBP_{I,J}(g_c) = \sum_{j=0}^{J-1} G(g_i - g_c)2^j \quad (7)$$

Where,

$$G(m) = \{0, m < 0; 1, otherwise. \quad (8)$$

At last, by feature extraction the extracted grape leaf image is given to the proposed WOA optimized XG Boost classifier.

3.4 Classification using WOA- XG boost classifier

In this proposed work Machine Learning method called WOA- XG boost classifier is utilized for effective classification.

3.4.1 XG boost classifier for grape leaf disease

XG-Boost is an ensemble learning method used for tasks like regression and classification. XG-Boost is based on the framework for gradient boosting. XG Boost mostly performs well on datasets that are tabular or well-structured. By adding a regularization component to the objective function, XG-Boost reduces the likelihood of over fitting in the model. It more precisely specify the loss function by doing a second-order Taylor expansion on the objective function as opposed to a first-order one. Figure 4 shows the XG Boost classifier.

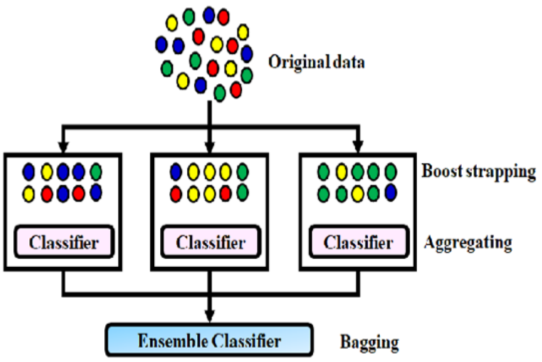

Figure 4: *XG boost classifier*

The following is an illustration of the output final prediction:

$$y_i = \varphi(x_i) = \sum KK = 1\ f_k(x_i), f_k = F \qquad (9)$$

Where the training set and the class labels that correspond to it are represented by $x_i$andy_i. The set of all regression trees and the leaf score for the k^{th} tree are denoted by $f_k$and F respectively. At this time, resultant to the condition at the layer, the data splits up into aggregating. One of the most important aspects of using XG-Boost is its capacity to manage large datasets and missing data efficiently. XG-Boost have several hyper parameters that adjusted to raise the model's performance level. To refine the parameters of XG Boost Classifier the proposed work introduces WOA.

3.4.2 Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) is a simple and effective metaheuristic optimization technique, stimulated by humpback whale hunting. WOA efficiently search throughout a whole solution space by mimicking humpback whale hunting techniques, such as encircling prey and using spiral-shaped bubble nets. It improves the algorithm's ability to search globally. An innovative mathematical program called the whale optimization algorithm mimics humpback whales' cooperative predation strategies.

The goal of humpback whales is to locate and identify their prey. The whale believes that this is the best way of action and instructs other whales to approach the target prey. The circular prey strategy is defined using equations (10) and (11)

$$H = |J.R^*(k) - R(k)| \qquad (10)$$

$$R(k+1) = R^*(k) - I.H \qquad (11)$$

In this case, k is the current iteration, R is the velocity location, and I and J are vectorial coefficients.The algorithm's in figure 5shows the three techniques for encircling prey are bubble-net attacking, searching for prey, and enclosing prey: If there are N whales in the population, then X_i(i {1, 2,..., N}) shows the position vector of the i^{th}whale, a single whale, and offers a feasible solution to a given optimization problem. Both low-level and high-level characteristics must be evaluated; therefore, the suggested method must be standardized.

$$R(k+1) = \begin{Bmatrix} R(k) - I.H & if\ P < 0.5 \\ H.e^{mn}.\cos(2\pi l) + R^*(k) & if\ P \geq 0.5 \end{Bmatrix} \qquad (12)$$

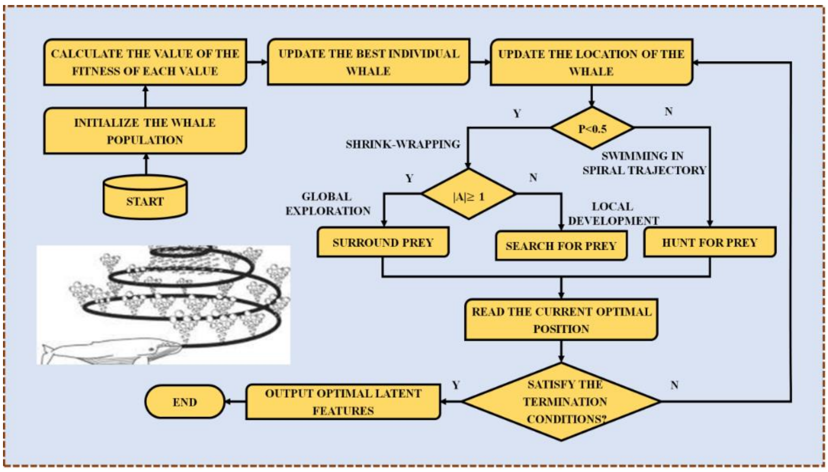

Figure 5: *Flow of Whale Optimization Algorithm*

Since it is impossible to predict the ideal in advance, when the population is initialized, the WOA method considers the best candidate solution to be the prey or approximate optimal. Once the preys (the ideal whale individual) have been found, other whales in the population change their postures to approach the prey over a number of cycles.

4. Result and discussion for grape leaf disease

Dataset is taken from kaggle.com for disease identification. Machine learning models are then applied to train grapevine disease dataset. Using python software the four classes of diseases are founded as black rot, ESCA, healthy, leaf blight.

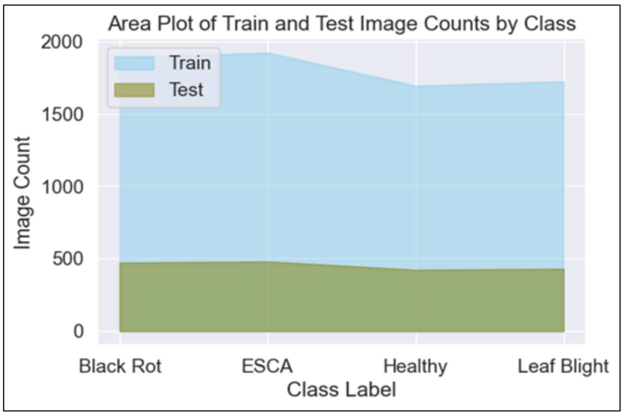

Figure 6: *Area plot of test and train image counts by class*

The area plot in figure 6 illustrates the distribution of train and test image counts across different grape leaf disease classes: Black Rot, ESCA, Healthy, and Leaf Blight. The X-axis denotes the class labels, whereas the Y-axis directs the number of images. The blue-shaded region corresponds to the training dataset, which consistently have a higher count than the test dataset, represented by the green-shaded region. This visualization helps to know the availability of data for training a grape leaf disease classification model.

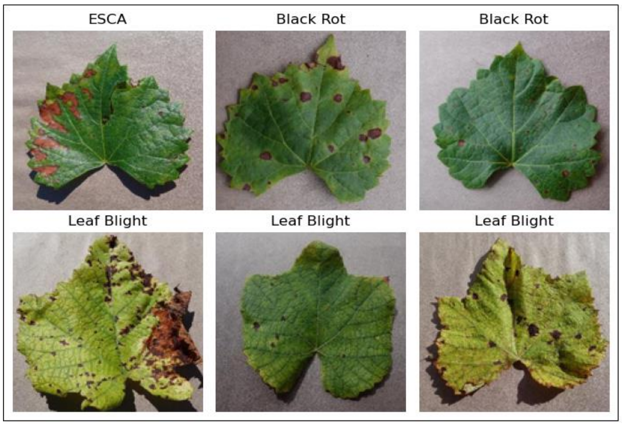

Figure 7: *Grape leaf disease sample images from grapevine disease dataset*

In figure 7 shows the sample grape leaf disease of ESCA, black Rot and leaf blight. Here the grape leaf disease by ESCA disease, black rot disease and light blight are by the sample image from the grapevine disease dataset. Each disease is shown as a sample image for identification,

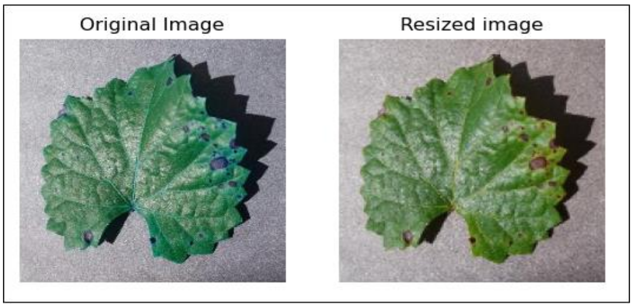

Figure 8: *Original and resized grape leaf disease image*

In Figure 8 the original grape leaf disease image is resized for further pre-processing technique is utilized. A perfect vision of input resized image is captured using image resizing.

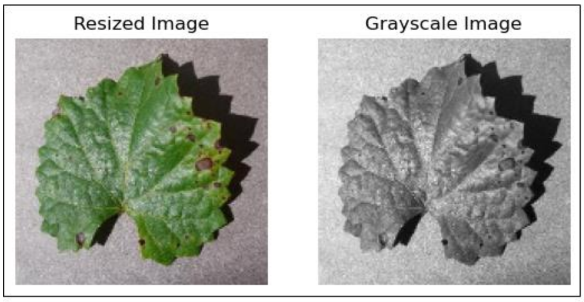

Figure 9: *Grayscale grape leaf disease image*

Two steps of pre-processing for grape leaf disease images are depicted in the provided image in Figure 9. Converting images to grayscale preserves important structural details while restructuring image processing.

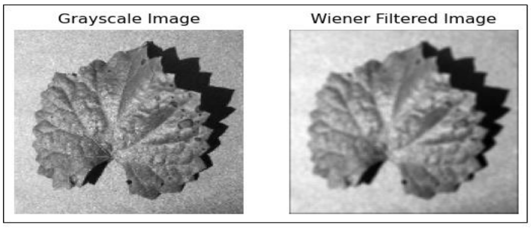

Figure 10: *Wiener filter image for grape leaf disease image*

After conversion of gray scale image, in figure 10 wiener filter is utilized to pre-process the grape leaf disease image to remove the unwanted noise which shows the flawless of the GLD image.

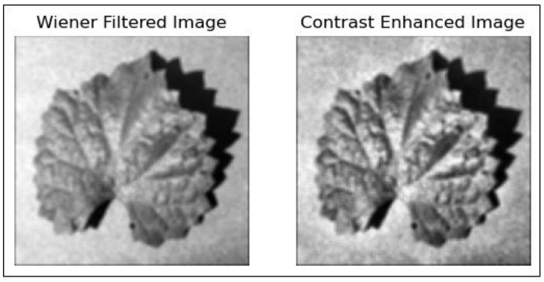

Figure 11: *CLAHE*

Figure 11 shows the CLAHE of grape leaf disease. Here CLAHE use the input as wiener filtered image and improve the quality of the unclear grape leaf disease image to enhance the contrast of the image.

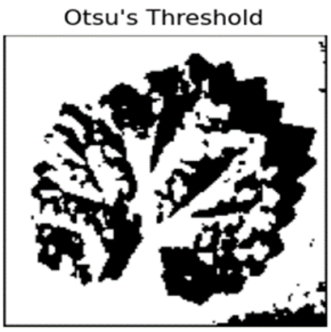

Figure 12: *Otsu's threshold for grape leaf disease*

Figure 12 illustrates the Otsu's segmentation is applied to a grape leaf disease image. Here the improved contrast image is used as an input to Otsu's segmentation the threshold values between the foreground and background is calculated using the pixel intensities

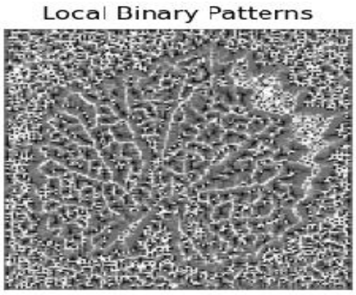

Figure 13: *Local Binary Pattern for grape leaf disease*

Figure 13 demonstrates the Local Binary Pattern applied to grape leaf disease. Using local binary pattern each pixel values are textured on the basics of local pattern. Because of this the binary values are changed as decimal values.

4.1 Performance metrics

By examining accuracy, precision, sensitivity, specificity, Area under the Curve (AUC), classification with "positive" and "negative" labels, the performance of each classification model in this study explained in table 1.

Table 1: *Performance metrics*

Performance metrics	Formula
Accuracy	$\frac{(TN+TP)}{TS}$
Precision	$\frac{(TP)}{TP+FP}$
Recall	$\frac{(TP)}{(TP+FN)}$
$F1-score$	$\frac{(2*\text{Precision}*\text{Recall})}{(Precision+Recall)}$

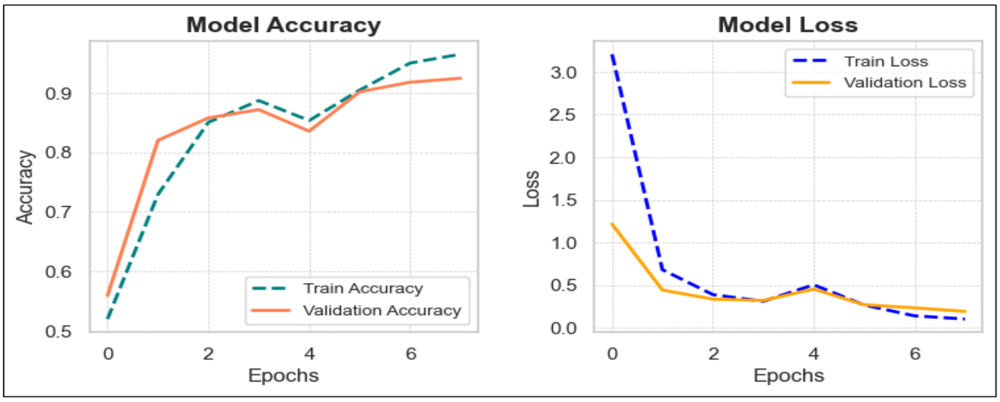

Figure 14: *Model accuracy and model loss for grape leaf disease*

Figure 14 shows the model accuracy and model loss of grape leaf disease. The model accuracy have train accuracy and validation accuracy. The X-axis denotes the epochs and y-axis is accuracy for model accuracy simultaneously for model loss X-axis for epochs and Y-axis for loss. The train accuracy is high when compared to the validation accuracy. The accuracy for the proposed method is 92.41%.

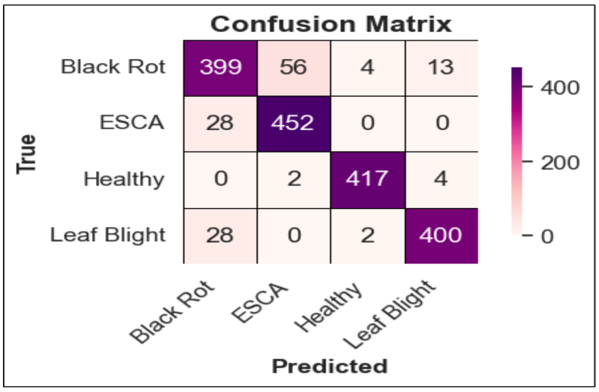

Figure 15: *Confusion matrix for grape leaf disease*

Based on a collection of experimental data with known true values, the confusion matrix is a table that assesses well a classification model performs in figure 15. For this investigation, the following definitions are given: False Negative (FN), False Positive (FP), True Positive (TP), and True Negative (TN) is calculated for Black Rot, ESCA, Healthy as well as Leaf Blight.

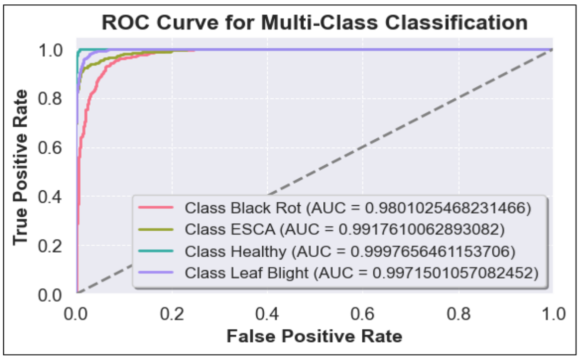

Figure 16: *ROC curve for multi-class classification*

According to the results shown in Figure 16, the supplement dataset significantly lowers the AUC value for class black rot of 0.98, class ESCA of 0.991 and leaf blight of 0.997. In comparison, the suggested WOA optimized XG Boost classifier continues to have the highest AUC value of 0.999 respectively.

4.2 Comparison for the proposed method

The comparison of the proposed method with existing method is presented in table 2. The Light weight CNN have the classification accuracy of 86.29% [21] and SCBO based DNFN have the accuracy of 92% [16]. The proposed WOA-XG Boost have the higher accuracy of 92.41% compared to the existing method in table 2.

Table 2 : *Comparison for the proposed method*

Study	Method	Accuracy
Lin *et al.* [21]	Light weight CNN	86.29%
Bajait *et al.*[16]	SCBO based DNFN	92 %

Proposed approach	WOA - XG boost	92.41 %

4.3 Comparisons for WOA optimized XG boost

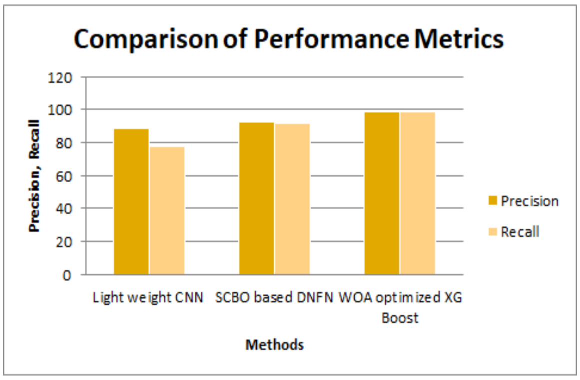

Figure 1: *Comparison of performance metrics*

The Precision and recall value for classifiers including light weight CNN, SCBO based DNFN and the proposed is presented in Figure 17. The Light weight CNN have the value of 77.76% and 88.63% [21] and SCBO based DNFN have the value of 92.5% and 91.7% [16]. The proposed WOA optimized XG Boost method have the precision value of 99% and recall of 99% for healthy grape leaf.

5. Conclusion

In this study, a WOA-XG Boost is advanced for the classification of GLD. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, texture enhancement, ensures that the input images are optimized for segmentation. The use of approximate Otsu's threshold for segmentation further enhances the precision of identifying threshold values in the images. Additionally, the Local Binary Pattern analyzed the local texture structure. The performance evaluation, conducted on the grapevine disease dataset, demonstrates the superior capabilities of the WOA-XG Boost compared to existing state-of-the-art methods. The improved accuracy of 92.41% is achieved as a higher accuracy when compared to the existing techniques.

Reference

1. Yun Peng; Shenyi Zhao; Jizhan Liu, Year: 2021, "Fused deep features-based grape varieties identification using support vector machine", Agriculture, Vol: 11, no: 9, pp. 869.

2. Miaomiao Ji; Lei Zhang; Qiufeng Wu, Year: 2020, "Automatic grape leaf diseases identification via United Model based on multiple convolutional neural networks", Information Processing in Agriculture, Vol: 7, no: 3, pp. 418-426.

3. Bin Liu; Cheng Tan; Shuqin Li; Jinrong He; Hongyan Wang, Year: 2020, "A data augmentation method based on generative adversarial networks for grape leaf disease identification", IEEE Access, Vol: 8, pp. 102188-102198.

4. Abdulridha Jaafar; Yiannis Ampatzidis; Sri Charan Kakarla; Pamela Roberts, Year: 2020, "Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques", Precision Agriculture, Vol: 21, pp. 955-978.

5. Jaafar Abdulridha; Yiannis Ampatzidis; Jawwad Qureshi; Pamela Roberts, Year: 2020, "Laboratory and UAV-based identification and classification of tomato yellow leaf curl, bacterial spot, and target spot diseases in tomato utilizing hyper spectral imaging and machine learning", Remote Sensing, Vol: 12, no: 17, pp.2732.

6. Haibin Jin; Yue Li; Jianfang Qi; Jianying Feng; Dong Tian; Weisong Mu, Year: 2022, "GrapeGAN: Unsupervised image enhancement for improved grape leaf disease recognition", Computers and Electronics in Agriculture,Vol: 198, pp.107055.

7. Zhou Changjian; Zhiyao Zhang; Sihan Zhou; Jinge Xing; Qiufeng Wu; Jia Song, Year: 2021, "Grape leaf spot identification under limited samples by fine grained-GAN", Ieee Access, Vol: 9, pp. 100480-100489.

8. M. Shantkumari; S.V. Uma, Year: 2021, “Grape leaf segmentation for disease identification through adaptive Snake algorithm model”, Multimedia tools and applications, Vol: 80, no: 6, pp. 8861-8879.

9. Aphichet Chaimanee; Xiaoli Fu; Guifen Lyu; Niwat Angkawisittpan; Nuttapon Chaiduangsri; Sivarit Sultornsanee, Year: 2023, “Improved Fuzzy C-means Clustering for Grape Leaf Disease Detection using Mathematical Morphology”, In 2023 International Electrical Engineering Congress (iEECON), pp. 391-394.

10. Seyed Mohamad Javidan; Ahmad Banakar; Keyvan Asefpour Vakilian; Yiannis Ampatzidis, Year: 2023, “Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning”, Smart Agricultural Technology, Vol: 3, pp. 100081.

11. RajinderKumar M. Math; Nagaraj V. Dharwadkar, Year: 2022, “Early detection and identification of grape diseases using convolutional neural networks”, Journal of Plant Diseases and Protection, Vol: 129, no: 3, pp. 521-532.

12. M. Shantkumari; S.V. Uma, Year: 2023, “Machine learning techniques implementation for detection of grape leaf disease”, Multimedia tools and applications, Vol: 82, no: 20, pp. 30709-30731.

13. K.Ashok kumar; S.Parthasarathy; S. Nandhini; K.Ananthajothi, Year: 2022, “Prediction of grape leaf through digital image using FRCNN”, Measurement Sensors, Vol: 24, pp. 100447.

14. A. Diana Andrushia; T. Mary Neebha; A.Trephena Patricia; S. Umadevi; N.Anand; Atul Varshney, Year: 2023, “Image-based disease classification in grape leaves using convolutional capsule network”, Soft Computing, Vol: 27, no: 3, pp. 1457-1470.

15. B.J. Prathiksha; Vijaya Kumar; M. Krishnamoorthi; P. Poovizhi; D. Sowmiya; B. Thrishaa, Year: 2024, “Early Accurate Identification of Grape leaf Disease Detection using CNN based VGG-19 model”, In 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC-ROBINS), pp. 263-269.

16. Vaishali Bajait; N. Malarvizhi, Year: 2024, “Grape leaf disease prediction using Sine Cosine Butterfly Optimization-based deep neuro fuzzy network”, Multimedia Tools and Applications, Vol: 83, no: 17, pp. 49927-49951.

17. Shtwai Alsubai; Ashit Kumar Dutta; Ahmed Hussein Alkhayyat; Mustafa Musa Jaber; Ali Hashim Abbas; Anil Kumar, Year: 2023, “Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease classification model”, Computers and Electrical Engineering, Vol: 108, pp. 108733.

18. M. Prabu; Balika J. Chelliah, Year: 2023, “An intelligent approach using boosted support vector machine based arithmetic optimization algorithm for accurate detection of plant leaf disease”, Pattern Analysis and Applications, Vol: 26, no: 1, pp. 367-379.

19. Navneet Kaur; V. Devendran, Year: 2024, “A novel framework for semi-automated system for grape leaf disease detection”, Multimedia Tools and Applications, Vol: 83, no: 17, pp.50733-50755.

20. Chuang Cai ; Qifan Wang; Weiwei Cai; Yixin Yang; Yahui Hu; Liujun Li; Yanfeng Wang; Guoxiong Zhou, Year: 2023, “Identification of grape leaf diseases based on VN-BWT and Siamese DWOAM-DRNet”, Engineering Applications of Artificial Intelligence, Vol: 123, pp. 106341.

21. Jianwu Lin; Xiaoyulong Chen; Renyong Pan; Tengbao Cao; Jitong Cai; Yang Chen; Xishun Peng; Tomislav Cernava; Xin Zhang, Year: 2022, “Grapenet: A lightweight convolutional neural network model for identification of grape leaf diseases”, Agriculture, Vol: 12, no: 6, pp.887.