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Automated Detection and Classification of Mango Fruit Diseases Using A Novel WOA-QRNN Technique on Infected Mango Fruit Images Through Transfer Learning

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Abstract: Mango Fruits are not only loved for their delicious taste but also valued for their rich nutritional content. This makes them an essential component of diverse diets all around the World. Despite their popularity, the mango industry faces significant challenges from diseases that impact mango trees and fruit quality, leading to reduced yields and economic losses for farmers. To ensure the sustainability of mango products, it is imperative to detect and manage these diseases effectively. By utilizing deep learning algorithms trained on images of healthy and diseased Mango fruits, researchers and farmers can accurately identify diseases at an early stage. Recent advancements in deep learning have enabled the classification and identification of mango fruit diseases from images of mangos. This study introduces an Automated Mango Fruit Disease Detection Using Whale Optimization with Quasi Recurrent Neural Network (WOA-QRNN) model, that is applied to infected mango images. The WOA-QRNN method focuses on leveraging deep learning to identify mango fruit diseases. To achieve those, the WOA-QRNN technique starts with image pre-processing using Bilateral filtering (BF) for noise reductions. Subsequently, adaptive threshold-based segmentation is applied, followed by feature vector generations using the VGG-16 model. The WOA algorithm is then employed as a hyperparameter optimizer. Finally, the Quasi-Recurrent Neural Network (QRNN) model is utilized for accurate disease identification and classifications in mango fruit. Experimental validations of the WOA-QRNN techniques are conducted using benchmark mango fruit image databases. The outcomes demonstrate the promising performances of the WOA-QRNN approaches compared to existing methods across various evaluation metrics. This research highlights the effectiveness of combining deep learning, with optimization algorithms for automated mango fruit disease detections.

Keywords: *Mango fruits, Diseases, Image processing, Deep learning, Quasi Recurrent Neural Network, Whale Optimization Algorithm.*

1. Introduction

Mangoes, scientifically glorified as Mangifera indica, are often called the "king of fruits" for their rich taste; unique flavor, and numerous health benefits. Indeed, mangoes are not only yummies but also packed with essential nutrients such as vitamins A and C, potassium, and fibers [1]. They have been staples in diets around the world for centuries and continue to be a popular fruit choice for many. In recent years, the mango industry has been facing challenges due to illnesses that affect mango trees and their fruits. These diseases – they can largely impact the quality and yields of the mango crops. Causing economic loss for the farmers and lesser availability of these beloved fruits for consumers. Thus, it's significant to detect and manage these diseases with efficiencies, to ensure the sustainability of mango production [2]. Deep learning is a sub-branch of artificial intelligence involving the training of neural networks to recognize patterns and make predictions based on huge amounts of data [3]. Utilizing deep learning algorithms, researchers and farmers could accurately identify diseases in mango fruits at a perhaps early stage [4]. Thus, enabling them to timely interventions and management strategies.

One of the primary advantages of using deep learning for disease detection in mango fruits is its ability to analyze images with high accuracy and quickly. Feeding the algorithm with images of both healthy and diseased mango fruits, it learns to tell the differences between the two and can provide real-time feedback on disease presence [5]. This helps farmers to take proactive measures to curb the spread of diseases and minimize crop losses. Furthermore, deep learning techniques could be utilized to fashion an automated system that continuously monitors, the mango orchards for symptoms of diseases [6]. By deploying drones that are outfitted with cameras and deep learning algorithms, farmers can efficiently survey extensive areas of mango trees – detecting any abnormals that may hint at the disease's presence. This proactiveness not only saves time and work but also assures early detection and treatment of diseased trees [7]. Additionally, the data collected through deep learning-based disease detection systems is utilized for gaining valuable insights into disease patterns and trends in mango orchards. This information helps researchers and agricultural experts to develop effective strategies for disease prevention and control [8].

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In recent studies, Convolutional neural networks (CNNs) effectively sort images of disease-ridden mango fruits [9]. CNNs are deep learning algorithms broadly used across varying applications - they shine in image classification tasks. This success has motivated our exploration to diagnose fruit diseases by utilizing DL models. The performance of CNNs heavily depends on their hyperparameters, which influence the training pathway directly. Choosing the right hyperparameters is critical for optimizing CNN training [10]. For instance, using a low learning rate might cause the network to ignore vital data details - meanwhile, a high learning rate could result in too speedily confluence. Thus, optimally tuning CNN hyperparameters ensures effective training and maximizes performance outcomes.

This article details a method titled Automated Mango Fruit Disease Detection Utilizing Whale Optimization with Quasi Recurrent Neural Networks (WOA-QRNN). It aimed at scanning images of mango fruits. The WOA-QRNN approach is aimed at detecting mango fruit diseases using deep learning (DL) principles. Firstly, in achieving the results, the WOA-QRNN method starts, by deploying Bilateral Filtering (BF) to prepare images. In addition, it employs an adaptative threshold-based segmenting and then generates feature vectors using VGG-16 with the Whale Optimization Algorithm (WOA), which acts like a hyperparameter optimizer. Finally, the QRNN model made its debut to accurately pinpoint and categorize diseases in mango fruits. The efficaciousness of the technique WOA-QRNN was evaluated by experimental validations, using benchmark mango fruit image datasets.

The Project is first introduced in Section 1. Then, a brief overview of a literature survey is provided in Section 2. Section 3 discusses the operation procedures for the proposed system and its implementations. The conclusions that have been drawn and the outcomes that were achieved are detailed in Section 4. Finally, Section 5, summarizes the findings and subtly suggests potential avenues for future research.

2. Related Works

This section will review some of the latest studies in picture dissection for fruit sorting, detecting diseases, and many classifications. It's seen widely that a typical approach to this research tends to make use of color and texture characteristics to sort fruits. Nonetheless, the majority of the research into fruit identification is planting its roots heavily in tree-based fruit types. Nowadays, current studies point out different techniques for classifying such varying fruit types and detecting diseases that might impact those fruits; Yet particulars on disease pinpointing in fruits are somewhat limited. Many types of research methods are discussed here to highlight the recent developments in those mentioned areas.

In reference number [11], they have been combining the use of Convolutional Neural Network (CNN) structures for snatching features and Histogram of Orientated Gradients (HOG) for getting the shape and texture information. Those extracted features are then fed into a Disease Classification model that helps with the exact identification of various diseases. This method is hailed for its high accuracy rates in disease identifications and classifying them, with the Hybrid between CNN and HOG model doing much better than just CNN methods alone, is particularly notable in stuff like the Mango disease detections and their classifications.

Further on, in [12], an economical method that includes a Vector Network Analyzer Tool comes into play. This melds together the K-nearest neighbors algorithms and the Neural Networks architectures. Author [13], introduces this unique strategy for predictions of mangos using a CNN and putting to work the binary cross-entropic strategies for reducing prediction losses. Also, [14] comes across a method that tidies up retail check-out processes by using not-too-heavy CNNs together with image processing this study brings to the table a dataset filled with three categories of fruits – boxed goods, not-boxed goods, and Random stuff. The Development of the CNN model that includes Stuff like RGB Color, Histogram, and centroid features obtained via K-means clustering is supposed to boost classification accuracy. These varying methods all contribute greatly towards the enhancement of the effectiveness of fruit sorting and disease detection by methods based on images.

According to the study [15], an input image was captured through a webcam, and saved in JPEG format, then it was subjected to 11 preliminary processing steps. The detection of whether mangoes are ripe or non-ripe was vaguely accomplished by analyzing color features that were extracted from mango images, and it was followed by a classification round. Using a digital camera in [16] was aimed at improving the quality of input image data! Various pre-processing tricks, stuff as resizing and, like, image enhancement is applied to spot the region of interest. Within a seconds-long window of 5, the system has effectively detected mango diseases by text feature extraction. The classification was done at the end, using SVM.

In research [17], they present a novel deep mutual learning model known as DVNet which combines the capabilities of DenseNet 121 and VGG19 neural networks for the detection of diseases in mango leaves. This study includes integration with hyperparameter optimization by using Particle Swarm Optimization (PSO), which is a methodical approach to finding the best parameter values. The literature [18] described uses some advanced image processing techniques; including pre-processing methods like background eliminations, and contrast enhancements to identify diseases in mangoes. It utilizes instance segmentations and specialized neural network architectures (CNN_FOA) with optimization through the FireFly Optimizer. This approach showcases a comprehensive method for automated disease detection in agricultural settings. They are leveraging cutting-edge technologies to improve crop health monitoring and management.

3. Proposed Work

The WOA-QRNN methodology follows a structure in its workflow, as shown in the illustrious Fig. 1. First, a Bilateral filter is used to get rid of noise, which makes the image clearer. Next up, an adaptive threshold-based segmentation method is used for segmenting. Afterward, feature extraction is done by utilizing the VGG-16 model. Finally, the hyperparameters of the Quasi-Recurrent Neural Network (QRNN) are tuned by WOA before the classification of diseases, and assignment of specific class labels. Details, which are more elaborated for each stage, are given in the following sections.

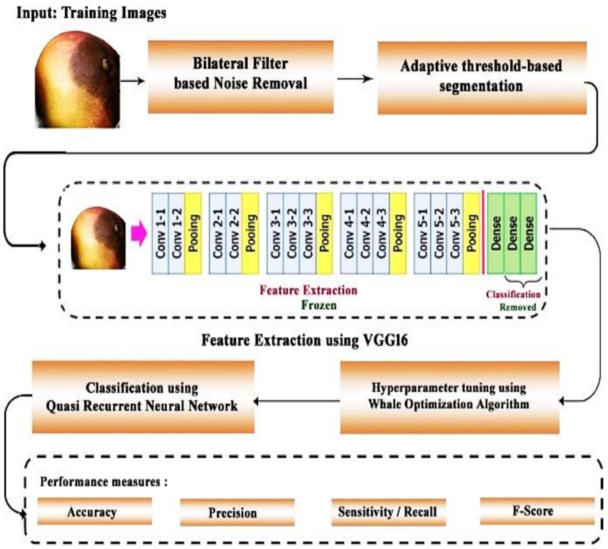

Fig.1. Overall framework of the WOA-QRNN approach

3.1 Bilateral Filter based noise removal

The bilateral filter is a widespread method used for noise reduction in image processing, particularly for disease detection and classification in mango fruits [19]. It effectively preserves edge while smoothing out noises; making it suitable for enhancing image quality before disease analysis as shown in Fig. 2.

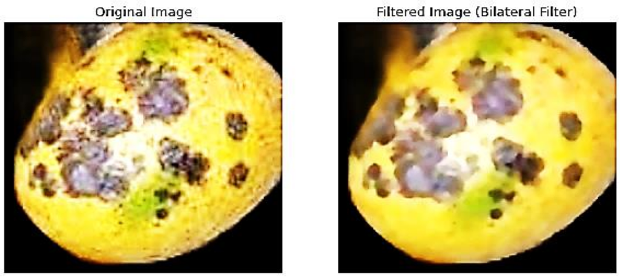

Fig. 2. Bilateral filter-based noise removed image

The Bilateral Filter is defined as shown in Eq. (1):

$$B(I)_p = \frac{1}{W_p} \sum_{q\epsilon\Omega} I_q \cdot g_{\sigma_s}(\| p - q \|) \cdot g_{\sigma_r}(| I_p - I_q) \quad (1)$$

Where,

- *B(I)* stands as the output pixel value on location p in that filtered image *B(I).*
- I_p and I_q are the intensity values at locations p and q in an input image I respectively.
- *Ω* is the signifies neighborhood of a pixel p which the filter is acting on.
- $g_{\sigma_s}(\| p - q \|)$ is the spatial Gaussian kernel; it determinates spatial similarity between pixels based on their distance $(\| p - q \|)$.
- $g_{\sigma_r}(| I_p - I_q |)$ is the range of Gaussian kernel, it considers the intensity differences $(| I_p - I_q |)$ for preserving edges while making the regions that show similar intensity.
- *Wp* is the Normalization factor, so the filtered value gets scaled properly.

In the context of mango fruit disease detection and classification:

- I_p represents the pixel intensity value of the mango fruit image.
- The Bilateral filter, is applied to 'I' to get a denoised image *B(I),* where noise is lower while keeping important image features like disease symptoms or textures.

3.2 Adaptive threshold-based segmentation

Adaptive thresholding plays a vital role in image processing by enabling object segmentations against a background. In the context of detecting and classifying diseases on mango fruits, this method is essentially for distinguishing between infected and healthy regions in mango images, as illustrated by Fig. 3.

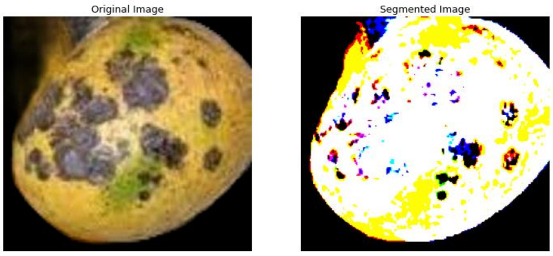

Fig.3. Sample Segmented Image

The fundamental concept of adaptive thresholding involves determining an individual threshold value for each pixel based on its local neighborhood rather than applying a uniform threshold to the entire image [20]. This method is particularly effective in situations where the image exhibits varying lighting conditions or inconsistent illumination. Initially, in Adaptive thresholding, the image is partitioned into smaller sections or grids, which can be square or rectangular. Subsequently, a specific threshold is assigned to each grid. This can be accomplished using various techniques such as calculating the mean, median, or Gaussian-weighted mean of the pixel values within each grid. Let's denote the threshold for a given grid as Tij, where i and j represent the coordinates of the grid. It can be represented as shown in the Eq. (2).

$$Output\ (x,y) = \begin{cases} 1 & if\ Image\ (x,y) > T_{ij}\ (x,y) \\ 0 & Otherwise \end{cases} \quad (2)$$

Where:

- *(x, y)* represents the coordinates of the pixel in the image.
- Output *(x, y)* is the binary image after thresholding.
- Image *(x, y)* is the intensity value of the pixel in the original image.
- T_{ij} *(x, y)* is the local threshold value computed for the grid containing the pixel at coordinates *(x, y).*

Adaptive thresholding is a method used to help break down pictures of mango fruits into different areas. This helps to spot and sort out diseases in the fruits using either deep learning techniques or other ways of processing images.

3.3 Feature Extraction using VGG-16

The VGG-16 architectures are a well-sophisticated deep-learner model composed of 16 layers, including convolutions; max-pooling, and fully connected layers. The model was originally trained on a vastly datasets, like ImageNet, to do general tasks related to image classification tasks [21]. It's skilled in identifying a broad range of object features - from texture and shape to patterns. Particularly in identifying diseases in mango fruits, the VGG-16; a pre-trained model, is pivotal as a feature-extracting tool. When mango fruit images are input into the VGG-16 models, it pulls activations from one of its intermediate layers. Usually proceeding the, fully connected layers; serving as feature vectors. These vectors hold advanced image representation, cataloging details on a variety of visual sequences and structures.

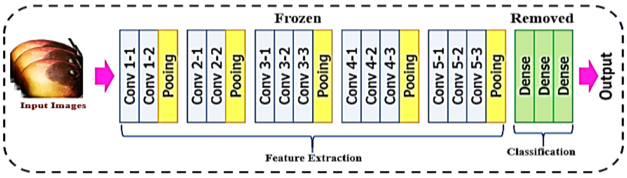

Fig. 4. VGG-16 as a feature extractor

Given that VGG-16 has been trained initially on a comprehensive dataset, it's equipped to undergo fine-tuning with a more focused dataset of mango fruit images tailored to disease Identification tasks by freezing the top layers - this allows the model to modify its features. Making them more relevant to the unique aspects of mango images and the diseases affecting them as depicted in Fig. 4. The feature vectors withdrawn are then fed into a classification algorithm. This classifying work links the extracted features with various mango disease categories, thus enabling it to distinguish between diseased and healthy mango fruits accurately, by employing this refined version of VGG-16. The detection of mango fruit diseases becomes more precise, leveraging the rich learning the model has achieved from extensive datasets to adapt to more specialized tasks.

3.4 Hyperparameter tuning using WOA

Next, the WOA makes adjustments to the hyperparameter values in the QRNN model. It's a metaheuristic strategy inspired by the hunting behaviors of some Humpback Whales [22]. They use a very intriguing method where they encircle their targets by swimming in what you could call a decreasing circle, eventually forming a spiral to create a bubble net. Mainly, WOA consists of exploit and exploration phases. In the phase of exploration, it involves searching for prey at random. In a time of the exploiting stage, humpback whales utilize a spiraling bubble-net technique for encircling their prey.

They update their locations based on the prey position and regard the whales like they are searching agents using Eq. (3) & (4). They make adjustments to control searching regions by using parameter vectors, A and also C, which governs local and global search behaviors using Eq. (5) & Eq. (6). The parameters are adjusted, to produce spiraled motions using Eq. (5); which enhances the effectiveness of their hunting strategy using Eq. (7).

$$D = \left| C.\vec{X}^{*}(t) - \vec{X}(f) \right| \quad (3)$$

$$\vec{X}(f+1) = \vec{X}^{*}(f) - \vec{A}.D \quad (4)$$

$$\vec{A} = 2\vec{a}\cdot\vec{r} - \vec{a} \quad (5)$$

$$\vec{C} = 2.\vec{r} \quad (6)$$

$$a = 2 - t\frac{2}{MAXIter} \quad (7)$$

The spiral-shaped path was conceived based on observations of, an optimal search agent's trajectory over distances ($X*$) and, the searching agent (X). After that, they went ahead and evaluated where the local searching agent was standing, based on Eq. (8). So, the parameter D is quantified by using Eq. (9). Eq. (10) then, can be utilized to model a spiral-shaped path. Also, the gradual reduction in encircling shapes, achieving somewhat of a 50% probability between them.

$$\vec{X}(f+1) = D.e^{bl}.\cos(2\pi l) + \vec{X}^*(f) \quad (8)$$

$$D = \vec{X}^*(f) - \vec{X}(f) \quad (9)$$

$$\vec{X}(t+1) = \begin{cases} shrinkingEncircling\ (Eq.(2))\ if\ (p < 0.5) \\ Spiral - shapedpath\ (Eq.(6))\ if\ (p \geq 0.5) \end{cases} \quad (10)$$

To enhance the exploration phase of the Whale Optimization Algorithm, (WOA) a random search agent is chosen to guide the search procedure. This search agent, known as Arbitrary A and represented by vectors, includes values that are either less than - 1 or greater than 1. These values have been used to steer the search agent away from known optimal solutions, helping in the exploration of the search space.

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \quad (11)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \quad (12)$$

In a given iteration pointed by the symbol Γ. We are on a hunt to catch an optimal solution symbolized by $\vec{X}^*$. Now, $\vec{X}$ is a location vector, and the A and C, are coefficient vectors that get used up in both exploitation and exploration phases. As the iterative process goes on, the vector A just linearly shrinks from two down to zero. The variable r is a random uniform distribution integer between [0,1]. D stands up for the best solution ever obtained. Hovering around somewhere, there's this parameter b; it's the master shaper of a logarithmic spiral. The value of 1, randomly in a zone stretching from [-1,1]. Meanwhile, P is a random variable switching spots within [0,1]. Over here, $\vec{X}_{rand}$ plays the role of a whale, randomly plucked from what's current in the population, as shown in the scribbles of Eq. (11) and Eq. (12).

The Fitness selection plays an important role in the Whale Optimization Algorithm (WOA). They utilize the encoded outcomes to generate better candidate solutions. Accuracy values are prime criteria, used to make up the FF in these contexts as shown in Eq. (13) & Eq. (14).

$$Fitness = \max(P) \quad (13)$$

$$P = \frac{TP}{TP + FP} \quad (14)$$

Where the outcomes of FP and TP define the false and true positive values.

3.5 Classification using QRNN

A Quasi-Recurrent Neural Network (QRNN) is a special type of neural network architecture that mashes up the strengths of recurrent neural networks (RNNs), and convolutional neural networks, (CNNs), for sequence modeling jobs [23]. The QRNNs are specifically great for tasks where both space and sequential information are important, like image classifications or sequence classifications. The structure of QRNN is depicted in Fig. 5. Every mango image is represented as matrices of pixel values. Mostly in the forms of RGB color conduits for colored pictures or grayscale intensity calculators for grayscale illustrations. Let us call a mango image input I, which was represented by a matrix $I \in \mathbb{R}^{H \times W \times C}$, here H is the height, W denotes widths, and C is the number of channels (like, 3 for RGB). In this study, VGG-16 was utilized, for extracting relevant features from mango images. The VGG-16 learns hierarchical representations of the image; capturing crucial visual patterns, and, structures. Let *f(I)* be the output feature representation, obtained from the CNN (VGG-16) when the input image *I*. This output, *f(I)*, may be showcased like a feature map, or sometimes a vector.

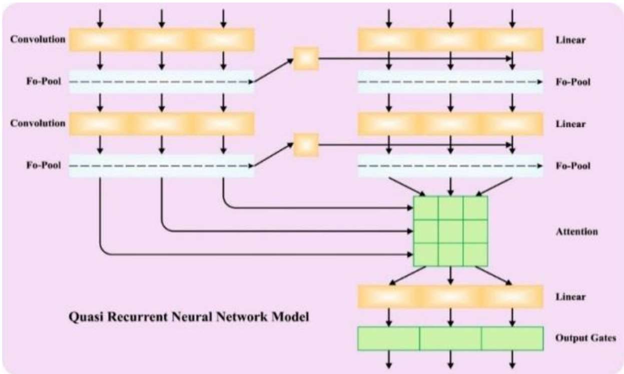

Fig. 5. Structure of QRNN

The extracted features *f(I)* are then fedded into a Quasi-Recurrent Neural Network (QRNN), for the sequence modeling and classifications. In a QRNN the input sequence- or feature sequence, in this case, is processed by using convolution operations mixed with recurrent operations, such as gated recurrent units or GRUs, to capture both spatial and Sequential dependencies within the feature representation. The QRNN processed the feature sequences *f(I)* to generate a sequence of hidden states, $\{h_t\}$, where each hidden state h_t is encoding information from previous states and the current input. The final hidden state, or maybe a sequence of hidden states from the QRNN is used for classifying ailments. Let us denote h_t as the last hidden state which was obtained from the QRNN. Often this hidden state, h_t, they get fed into a fully connected layer, maybe followed by a softmax activation, to predict the probability distribution over various disease classes.

The classification output $\hat{y}$ can be computed as shown in Eq. (15):

$$\hat{y} = softmax\,(Wh_t + b) \tag{15}$$

Where W is the weight matrix and b is the bias vector of the final fully connected layer.

The QRNN gets training from start to finish by using a supervised learning method, where the model parameters—like the CNN weights and QRNN weights—are maximized to minimize a loss function between the prediction probabilities $\hat{y}$ and the ground truth labels y (disease classes). The training process involves the backward propagation through time (BPTT) to update the model waits and optimize classification performance.

4. Experimental Results

4.1 Implementation Setup

Validation experiments are carried out to evaluate the effectiveness of the WOA-QRNN strategy in identifying and categorizing mango fruit sickness through the analysis of images of the infected fruits, they considered many elements. The testing has been conducted by using Python 3.6.5 in a computer system that features an i5-8600K processing unit, 250GB SSD, GeForce 1050Ti 4GB GPO, 16GB RAMs, and also a 1TB HDD. The performance evaluation of the - WOA-QRNN models has included analyzing key matrices like sensitivity, specificity, precision, accuracy plus F-score. For assessments, a well-known Kaggle dataset containing images of diseased mango fruits [24] was utilized. Specific trial examples for each classification are depicted in Fig. 6, along with the corresponding samples quantified shown detailed in Table 1.

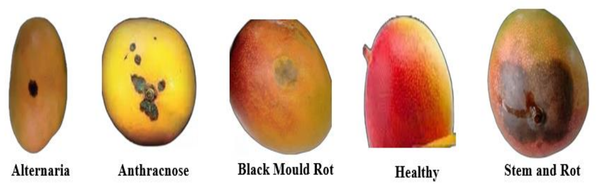

Fig. 6. Sample Dataset Images

Table 1. Dataset Description

Class	No.of. Samples
Alternaria	165
Anthracnose	129
Black Mould Rot	182
Healthy	205
Stem and Rot	157
Total	**838**

4.2 Discussions and Observations

In Fig. 7, the confusing matrix shows contentious classifications made by the WOA-QRNN model across different disease classes on mango fruits. The evaluations of the WOA-QRNN model, as seen in Table 2 and Fig. 8, highlight its effects in diagnosing mango fruit diseases within, both, training and testing datasets. The research used a 70% to 30% split between training and testing data. Exceptionally, the model shows exceptional performance in recognizing diseases in mango fruits, achieving high metrics such as - an F-score of 98.30%; an overall accuracy of 99.29%; a sensitivity of 99.07%, and a precision of 98.41%.

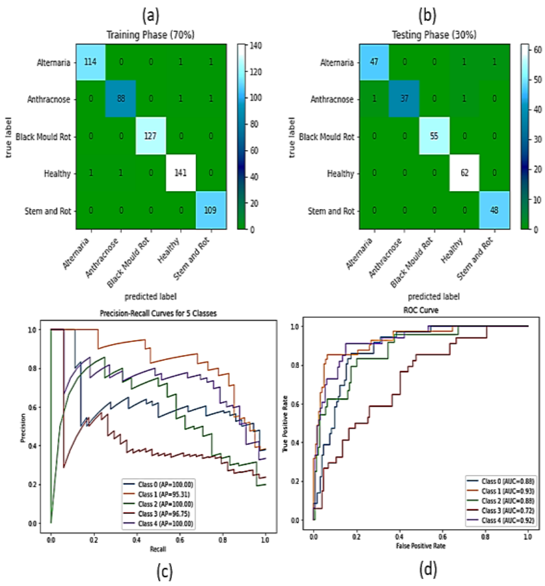

Fig. 7. (a) Confusion Matrix based on TR set (b) Confusion Matrix based on TS set (c) Precision-Recall Curve (d) ROC Curve

Table 2. Outcomes of the WOA-QRNN model for mango fruit disease classification

Class	Accuracy (%)	Precision (%)	Sensitivity (%)	F-Score (%)
Training Phase (70%)				
Alternaria	96.92	100.00	88.24	93.75
Anthracnose	98.46	92.31	100.00	96.00
Black	100.00	100.00	100.00	100.

Mould Rot				00
Healthy	98.46	93.75	100.00	96.77
Stem and Rot	100.00	100.00	100.00	100.00
Average	**98.77**	**97.21**	**97.65**	**97.30**
Testing Phase (30%)				
Alternaria	98.00	100.00	98.24	96.75
Anthracnose	98.46	95.31	100.00	97.00
Black Mould Rot	100.00	100.00	100.00	100.00
Healthy	100.00	96.75	100.00	97.77
Stem and Rot	100.00	100.00	97.15	100.00
Average	**99.29**	**98.41**	**99.07**	**98.30**

Table 3 illustrates the outstanding performance of the WOA-QRNN model as it is demonstrated by a detailed comparative analysis. This Table, briefly evaluates accuracy and other metrics for a WOA-QRNN model, comparing it to prior studies. According to Table 3, the accuracy of the [18] models has ranged from 95.00% to, 97.00%, while WOA-QRNN outperformed with a score of 99.29%. The Sensitivity values of such models ranged between low 82.00% and high 94.03%—however, the proposed model, well, scored higher, that's about 99.07%. The precision values for the models presented in [18] were varying from 92.00% up to 95.00%. However, our proposed model does better, achieving a superior precision of about 98.41%. Moreover, when analyzing the F-scores shown in Table 3, the models mentioned in [18] scored F-scores ranging widely from 68.00% to 94.02%, On the contrary, our suggested WOA-QRNN model showed an exceptionable performance, with an F-score was standing at 98.30%. Finally, Fig. 9 will illustrate a visual comparison of our proposed model alongside the existing models.

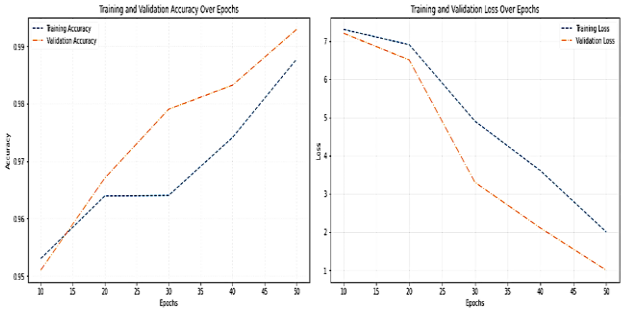

Fig. 8. Accuracy & Loss graph based on training and testing set

Table 3. Assessment of the Proposed model in Comparison to Existing models

Models	Accuracy (%)	Sensitivity (%)	Precision (%)	F-Score (%)
CNN-HOG	95.00	82.00	92.00	68.00
CNN	82.00	79.00	93.00	63.00
L-CNN	86.00	69.00	78.00	57.00
CNN-FOA	97.00	94.03	95.00	94.02
Proposed WOA-QRNN	**99.29**	**99.07**	**98.41**	**98.30**

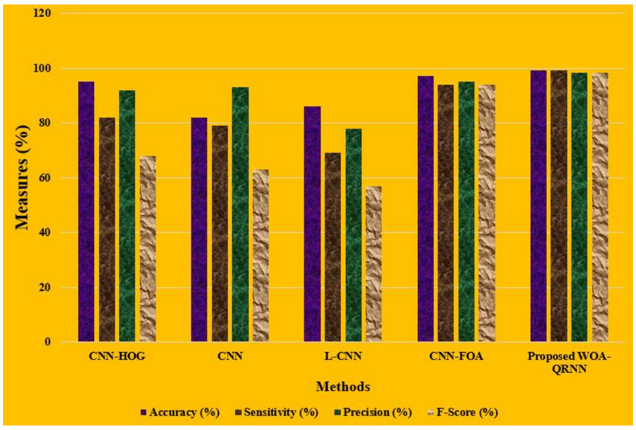

Fig. 9. Overall Comparative Analysis of the Existing Models with Proposed Model

5. Conclusion

Besides the highlighted performative metrics, it is crucial to underline that the WOA-QRNN model's exceptional accuracy, recall, precision, and F-scores attested to its robustness and reliability in addressing complexities associated with the identification of mango fruit diseases.

The model's precise disease categorization enabling early and accurate detections of affected mango fruits, assisting swift interventions for containing disease spreads, and minimizing crop yield losses. Furthermore, the proposed WOA-QRNN model exhibits scalability and flexibility, rendering it proper for deployment throughout diverse agricultural settings and geographic regions. Its efficacy in disease classifications enhances agricultural management practices and holds promises for broader application within the agricultural sector, contributing to overall food sustainability and security. Moreover, the integration of advanced computational techniques such as the Whale Optimizations Algorithm (WOA), and ensemble methods like Quasi Recurrent Neural Networks (QRNN) on the WOA-QRNN model, underscores the potential for leveraging innovating methodologies to address agricultural challenges. This interdisciplinary approach fosters innovations in agricultural research and opens avenues for developing tailored solutions to intricate agricultural issues. Future enhancements, for the proposed WOA-QRNN model include increasing datasets through data augmentations, exploring transferring learning for regional customizations, investigating sensor integrations for real-time disease detections in the agricultural field; and collaborating with stakeholders for validations and ongoing improvements in real-world scenarios.

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