A Single Stream Modified MobileNet V2 and Whale Controlled Entropy Based Optimization Framework for Citrus Fruit Diseases Recognition

MUHAMMAD HASSAM¹, MUHAMMAD ATTIQUE KHAN¹, (Member, IEEE), AMMAR ARMGHAN², SARA A. ALTHUBITI³, MAJED ALHAISONI⁴, ABDULLAH ALQAHTANI⁵, SEIFEDINE KADRY⁶, (Senior Member, IEEE), AND YONGSUNG KIM⁷

¹Department of Computer Science, HITEC University, Taxila 47080, Pakistan
²Department of Electrical Engineering, College of Engineering, Jouf University, Sakakah 72388, Saudi Arabia
³Department of Computer Science, College of Computer and Information Sciences, Majmaah University, Al-Majmaah 11952, Saudi Arabia
⁴Computer Sciences Department, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh 11671, Saudi Arabia
⁵College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, Al-Kharj 16278, Saudi Arabia
⁶Department of Applied Data Science, Noroff University College, 4612 Kristiansand, Norway
⁷Department of Technology Education, Chungnam National University, Yuseong-gu, Daejeon 34134, South Korea

Corresponding author: Yongsung Kim (kys1001@cnu.ac.kr)

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ABSTRACT

Fruit disease recognition is quickly becoming a hot topic in the field of computer vision. The presence of plant diseases not only reduces fruit production but also causes a significant loss to the national economy. Citrus fruits help to strengthen the immune system, allowing it to fight off diseases such as COVID-19. Manual inspection of fruit diseases with the naked eye takes time and is difficult; therefore, a computer based method is always required for accurate recognition of plant diseases. Several deep learning techniques for recognizing citrus fruit diseases have been introduced in the literature. Existing techniques had several issues, including redundant features, convolutional neural network (CNN) model selection, low contrast images, and long computational times. In this paper, single stream convolutional neural network architecture is proposed for recognizing citrus fruit diseases. In the first step, data augmentation is performed using four contrast enhancement operations: shadow removal, adjusting pixel intensity, improving brightness, and improving local contrast. The MobileNet-V2 CNN model is selected and fine-tuned in the second step. Using the transfer learning process, the fine-tuned model is trained on the augmented citrus dataset. The newly trained model is used for deep feature extraction; however, analysis shows that the extracted deep features contain little redundant information. As a result, an improved Whale Optimization Algorithm (IWOA) is used in the third step. The best features are then classified using machine learning classifiers in the final step. The augmented citrus fruits, leaves, and hybrid dataset were used in the experimental process and achieved an accuracy of 99.4, 99.5, and 99.7%. When compared to existing techniques, the proposed architecture outperformed them in terms of accuracy and time.

INDEX TERMS

Citrus diseases, augmentation, deep learning, feature selection, classification.
off diseases [3]. Citrus fruits not only provide cough relief but also help to improve the digestive system [4]. However, several factors such as climate change, arable land, and new diseases are the main obstacles to food production. Plant diseases have an impact on the quality and quantity of food produced [5]. Therefore, it is essential to diagnose the fruit diseases at the initial stage. The major citrus leaf disease are citrus black spot, citrus bacterial canker, citrus blight, citrus scab, and greening [6], [7]. The manual diagnosis techniques are based on the naked eye and always dependent on the expert person. This process not only consumes more time but also required an handsome amount [8].

Recently, the researchers of computer vision introduced automated techniques that are essential for the diagnosis of fruit diseases without human intervention [9]. The automatic detection and classification of fruit diseases are necessary as it not only save the fruits and plants from being infected but is also helpful in order to increase agricultural yields [10]. The computer vision techniques based on some important steps such as preprocessing of raw images, disease segmentation using image processing techniques such as K-Means, saliency methods, and many more, features extraction (i.e. color, shape, and texture), reduction of redundant features, and finally classification using machine learning classifiers (i.e. support vector machine, K-nearest neighbor, and named a few more). Super pixel clustering, histogram of orientation gradient (PHOG), and K-mean clustering are few image processing techniques [9]. The techniques that followed these steps, improve the accuracy when the smaller dataset is available. However, for the large imaging datasets, these techniques not performed well and reduce the classification accuracy.

Various deep learning techniques depending on convolutional neural network (CNN) have been introduced to recognize fruits and plants diseases [11]. Deep Learning is a subset of machine learning which employs series of techniques to represent greater abstractions in data [12]. These methods create a layered, combinatorial learning and representation architecture. Deep learning techniques are recognition methods that have several layers of representation [13]. These are generated by constructing simple but non-linear components which successively change a presentation at one level into a representation at a higher and slightly more abstract level. By combining enough of these modifications, more complex functions can be learned. The advancements in the field of deep learning have helped a lot in solving complex problems for several applications such as object classification, medical and agriculture [14], [15].

In recent years, researchers of computer vision introduced many techniques for citrus diseases recognition. Most of them focused on the hybrid techniques for the recognition tasks such as features are extracted from multiple sources and finally fused [6], [16]. Using this process, several irrelevant features are added. Also, a few redundant features are added during the fusion process that is later impacting the recognition accuracy. Feature selection is a crucial stage in agriculture and medical domains. It also minimizes computation cost and increases accuracy of classification. On the other hand, the feature selection procedure is complicated by three issues caused by small samples and large datasets. First, given limited datasets and complexity, feature selection is unstable. Secondly, with large datasets, feature selection takes longer. Finally, a certain feature selection approach may not provide adequate classification efficiency. As a result, a variety of parameters must be addressed while choosing an effective feature selection approach for classification tasks with limited samples [17]. Moreover, during the selection of the most optimum features, a few important features are also ignored. The main reason is the use of selection criteria like static parameters. Therefore, in this article, fusion and selection challenges are considered and proposed a new framework based on the deep learning and improved whale optimization algorithm. Our major contributions are listed as follows:

- Data augmentation is performed in the first step based on four contrast enhancement operations such as shadow removal, adjusting pixel intensity, improving brightness, and improving local contrast.
- Fine-tuned the MobileNet-V2 CNN model and freeze the 50% layers instead of all layers except newly added layers- New_FC, New_Softmax, and New_Output. After that, trained a network on augmented dataset using transfer learning. Features are extracted of the layer before fully connected.
- Proposed an improved whale optimization algorithm for the selection of best features for final classification.

The rest of this manuscript is organized in the following order: Related work which includes the summary of recent studies presented in Section 2. Proposed methodology in terms of detailed mathematical modeling described in Section 3. Results and comparison with existing techniques described in Section 4. Finally, conclude this manuscript under section 5.

II. RELATED WORK
In literature, various methods have been implemented for recognition of fruits diseases. Janarthan et al. [18] presented an automated system for citrus disease identification using limited data. They presented a patch-based identification network for accurately detecting citrus diseases which also includes an embedded module, cluster prototype module and simple neural network classifier. In terms of detection accuracy of the model that was 95.04%, the presented technique outperforms existing state-of-the-art methods.

Arooj et al. [19] presented an automated system by using computer vision techniques to identify citrus diseases. The proposed method contains five stages such as preprocessing, segmentation, feature extraction and reduction, fusion, and classification. Initially, noise in the images was removed and opted watershed algorithm for infected regions detection. In the next step, shape, color and texture features are extracted from the infected regions and serially fused. At the end,
multi class SVM classifier is employed for final classification. The datasets used was Citrus Image Gallery, Plant Village and self-collected and achieved average accuracy of 95.5%. Shuli et al. [20] presented a weekly DenseNet16 CNN framework for the identification of citrus diseases. The presented method was performed well even it can easily be used in mobile phones. Based on the obtained results, the weakly DenseNet16 network had shown the improved accuracy with minimum parameters. Moreover, they used the reusing process to overcome the difficulty in optimization. Mehedi et al. [21] presented an automated system for the categorization of images of citrus fruits. They have categorized two fruits - orange and Kinnow. In the presented method, the authors first collected the images of Orange and Kinnow and then applied preprocessing on the images. After that the segmentation and edge detection techniques were applied to segment the images of fruits. After that, three different CNN models are applied for final recognition and obtained best accuracy of 92.25%. Muhammad et al. [22] presented an automated deep learning based system for fruits diseases classification. They considered the problems such as similarity among infections of different fruit diseases and developed a deep-convolutional neural network for accurate classification. The authors considered five diseases such as black rot, scab, rust, powdery mildew, and bacterial spots. Based on the experimental process, the presented method showed the improved accuracy. Khan et al. [23] presented a novel method for two types of fruits disease classification such as apple and grapes. They considered the challenges such as convex edges, inconsistency between colors, irregularity, visibility, scale, and origin. To resolve these challenges, they introduced an end-to-end system which is based on contrast stretching, identification of diseases, feature extraction and fusion, feature selection and classification. Firstly, an adaptive and quartile deviation based infected regions are detected and obtained the binary images. Later, fusion is performed using weighted coefficient of correlation (CoC). After that, useful features are selected by using entropy and rank-based correlation approach that finally classified using multi-class support vector machine. The presented method achieved an accuracy of 97.7% that was improved than the recent studies.

End-to-end architectures based on deep learning have been used to classify plant diseases. For the classification of plant diseases, traditional machine learning techniques require a step called handcrafted feature extraction, whereas deep learning extracts automated features from raw images. Furthermore, traditional techniques extract features from binary images that are unnecessary in deep learning. Furthermore, the techniques mentioned above do not focus on optimizing extracted features, whereas in our work, we proposed an improved optimization algorithm for best feature selection.

III. PROPOSED METHODOLOGY

The proposed methodology for recognizing citrus fruits diseases consists of series of steps such as i) pre-processing; ii) region of interest (ROI) detection; iii) feature extraction; iv) features selection, and v) recognition. Initially, data augmentation is performed using four types of contrast enhancement techniques such as shadow removal, adjusting pixel intensity, improving brightness, improving local contrast. After that, MobileNet V2 deep model is employed and fine-tuned. The fine-tuned model is later utilized and trained using transfer learning process. In the later step, features engineering is performed and obtained a feature vector. The extracted deep features vector is optimized using an improved whale optimization algorithm. The best selected features are finally classified using neural network. The overall architecture of proposed framework is shown in Figure 1.

A. DATASETS

In this work, publicly citrus fruits diseases images database has been utilized for the validation. This database consists of three datasets such as: Hybrid Dataset, Citrus Fruits Dataset, and Citrus Leaves Dataset [24]. These datasets consists of total five classes including four diseases and one healthy. The images of these datasets are captured by using the single camera and the format of the images is JPG. The disease classes are black spot, canker, scab, greening and melanosis. A brief description about number of images in each class is presented in Table 1 and a few sample images are illustrated in Figure 2.

### Table 1. Summary of selected dataset diseases in terms of number of images.

| Disease      | Citrus Leaves | Citrus Fruits | Hybrid |
|--------------|---------------|---------------|--------|
| Disease      | Images        | Disease Images| Disease Images |
| Black Spot   | 170           | 20            | 190    |
| Canker       | 162           | 80            | 242    |
| Greening     | 200           | 15            | 215    |
| Melanosis    | 15            | 15            | 30     |
| Healthy      | 60            | 24            | 84     |
| Total        | 607           | 154           | 761    |
B. DATA AUGMENTATION

In machine learning, data augmentation is the process of increasing the size of original data by employing several operations such as flip, rotation, etc. [25]. As mentioned in Figure 1, deep learning model is employed for the feature extraction; therefore, to train a deep learning model, a handsome amount of training data is widely required. The selected citrus fruit dataset consists of limited number of images; therefore, it is essential to improve the dataset size using data augmentation process. Total three different types of citrus fruits datasets are available such as Hybrid Dataset, Citrus Fruits Dataset, and Citrus Leaves Dataset [24].

In this work, we utilized four contrast enhancement operations instead of simple flip and rotation operations. The performed operations are shadow removal, adjusting pixel intensity, improving brightness, and improving local contrast. These enhancement operations have been applied on each image of all classes. Mathematically, these operations are applied on the image as follows: Consider, the original input image \( I \) that is inverted by Eq. 1:

\[
Q^c (a) = 255 - I^c (a) \tag{1}
\]

where, the RGB color channel is represented by \( c \), original input image is represented by \( I^c \) for \( c \) channel of pixel \( a \). For the inverted image, \( Q^c \) is the similar intensity as illustrated in Eq. 2 for hazy image.

\[
Q (a) = P (a) s (a) + K (1 - s (a)) , \tag{2}
\]

where, global atmospheric light is represented by \( K \), the intensity of the pixel \( a \) is represented by \( Q (a) \), and intensity of original objects is denoted by \( P (a) \). The percentage of the emission of light from the objects is described by \( s (a) \). When there is a comparable or homogenous atmosphere, then \( s (a) \) can be expressed by Eq. 3:

\[
s (a) = x^{-\beta e(a)} \tag{3}
\]

The atmosphere’s scattering coefficient is represented by \( \beta \) and pixel \( a \) is scene depth and denoted by \( e(a) \). In the similar image, when \( \beta \) is constant, \( s (a) \) is determined by \( e(a) \).

\[
s (a) = 1 - \varphi min_{\{r,g,b\}} (min_{\{c\}} (Q^c (\frac{c}{K_c}))) \tag{4}
\]

\[
P (a) = \frac{Q (a) - K}{s(a)} + K , \tag{5}
\]

The value of \( s (a) \) is further refined using a threshold function, given in Eq. 6.

\[
M (a) = \begin{cases} 
2s (a) , & 0 < s (a) < 0.4 \\
1 , & 0.5 < s (a) < 1 
\end{cases} \tag{6}
\]

By employing \( M (a) \), the recovery equation is described as follows:

\[
P (a) = \frac{Q (a) - K}{M (a) s(a)} + K \tag{7}
\]

These operations are performed on each image separately for all three selected datasets. The target images of each class for all three datasets are 3000; therefore, these operations are performed multiple times. A few sample images of augmented dataset are shown in Figure 3. Based on this figure, it is clearly illustrated that for each image, four different images are obtained. Later, the augmented datasets are utilized for the training of deep models.

C. CONVOLUTIONAL Neural Network

Convolutional neural network is a deep learning algorithm, take an input image of a suitable size, and assign some weights and bias to different one object from others [26]. A simple CNN model consists of several important layers such as convolutional layer, activation layer named ReLu, pooling layers, fully connected layer, and softmax classifier [27]. Initially, image is acquired and passed to input layer. Each input passed to the hidden layers as mentioned above extract features. Consider, an input matrix \( I_m \) and \( O \) as output and assume that there occur a set of neurons \( K_j \), \( \forall_j \in [1, 2, 3, ..., j] \) then after the first stage, convolution output \( H (j) \) will be:

\[
H (j) = L \otimes K_j , \forall_j \in [1, 2, 3, ..., j] \tag{8}
\]
The dot product of filter and inputs is denoted by the convolution operation \( \circ \). Secondly, to establish a new 3D activation map, all \( H(j) \) activating patterns are layered together [50].

\[
G = E[H(1), H(2), \ldots, H(j)]
\]  
(9)

The result of this layer is returned in matrix form containing positive and negative values. The negative values are not required for next step; therefore, an activation layer commonly known as ReLU activation layer is applied. The importance of this layer is that it kept positive values and changes the negative ones into zeros.

\[
f(k) = \text{max}(0, k)
\]

ReLU \( T \) = \[
\begin{cases} 
0 & \text{if } T < 0 \\
1 & \text{if } T \geq 0
\end{cases}
\]  
(10)

Another layer named pooling layer helps in minimizing spatial size of an image. In a pooling layer, various operations are being applied namely, average pooling, max pooling, and min pooling, as illustrated in Figure 4.

![Figure 4. An example of max pooling, average pooling.](image)

The most important layer is fully connected layer, typically is made up of neurons that are completely interconnected to all previous layers of activation. The activations can then be computed using matrix multiplication and biased offset. Finally, the Softmax classifier is used to evaluate the layer’s efficiency.

\[
\mu \left( \frac{e^o}{\sum_{k=1}^{m} e^o} \right) f = \frac{e^o}{\sum_{k=1}^{m} e^o} 
\]  
(11)

As an input, positive, zero and negative real numbers are taken by softmax function and applying it to all \( q_i \) values. Each value is used as an input vector in an exponential function. A simple overall architecture of CNN based citrus fruit diseases recognition is illustrated in Figure 5.

![Figure 5. Simple structure of a CNN for citrus fruits disease recognition.](image)

### D. MODIFIED MobileNetV2

MobileNetV2 [28] model used for scalability and also uses the depth wise separable convolutions technique, which not only leverages linear constraints to overcome the problem of data loss in non-linear layers in convolution blocks, but also provides a new structure called inverted residuals to retain the information [29]. Moreover, MobileNetV2 model was based on the MobileNetV1 architecture, and it overcomes the problems associated with nonlinear systems in the model’s narrow layers that include building components. In comparison to its predecessor, the MobileNetV2 includes two new features: i) some constraints can appear linearly between layers; ii) second is the development of shortcuts between bottlenecks [30]. In this work, we modified this model based on the remove some layers and add some new layers. The last fully connected layer have 1000 object classes; therefore, we removed that layer and rest of the connected layers and added three new layers named: New_FC, New_Softmax, and New_Output. After that, several hyper parameters are initialized such as learning rate 0.05, epochs 100, drop out factor is 0.5, mini batch size is 32, and training method is rmsprop (Root Mean Square Propagation). This modified model is finally trained using concept of transfer learning. Transfer learning is a process of using a pretrained model for another task. In this work, the transfer learning is utilized to train a modified model for citrus diseases recognition.

**Domain:** The feature space \( F_s \) of \( d \) dimensions and random variables \( R(V) \) of \( F_s \) is obtained by domain \( D \), where \( V = \{v1, v2, v3, \ldots, vn\} \in F_s \). More precisely in transfer learning, the domain having identified information is termed as source domain and is represented by \( SD \) whereas, the target domain is that in which the domain will have the unidentified information, it is represented by \( TD \).

**Task:** The task is a learner objective in which the labeled region \( R \) and projection function \( f(\cdot) \) (can also be written as \( R(Z|V) \), means the probability of \( Z \) in the presence of \( V \)) is being contained, where \( Z = \{z_1, z_2, z_3, \ldots, z_n\} \in \mathbb{R} \). As per the definition of the task, the labeled area of the input space and the targeted region are represented as \( RS \) and \( RT \), respectively. Hence, the transfer learning is defined as follows:

Transfer Learning: The learned information is commonly represented as \( Z \). Labels and their relevant features create
data in this domain, which can be represented by \( D = \{(v1, z1), (v2, z2), \ldots, (vn, zn)\} \). According to the discussion above; the transfer learning can be defined by the following definition.

Given a source domain \( RS \) and a target domain \( RT \). Tasks of \( RS \) and \( RT \) given as \( Ts \) and \( TT \), where \( RS \neq RT \) and \( Ts \neq TT \). Transfer learning’s aim is to use the knowledge in \( RS \) to help learn the knowledge in \( RT \), where \( RS = \{Vs, R(Vs)\}, RT = \{VT, R(VT)\}, Ts = \{Zs, R(Zs|Vs)\}, TT = \{ZT, R(ZT|VT)\} \) [31]. Visually, this process is shown in Figure 6. In this figure, it is described that the original pre-trained model was trained on ImageNet dataset that having 1000 object classes. Therefore, we utilized the modified deep model and transfer knowledge using transfer learning. After that, trained new model on augmented citrus datasets and obtained a new learned model that later utilized for features extraction. Features are extracted from global average pooling layer of modified trained model and obtained a feature vector of dimensional \( N \times 1280 \). Analysis of obtained feature vector described that few of features are redundant and several of them are not relevant for final classification.

![Training from scratch](image1)

**E. FEATURE SELECTION**

Feature selection is an important step in the computer vision applications to minimize the computational cost and increase accuracy of classification tasks [32]. However, the feature selection procedure is unsuitable for limited datasets, but in this work, we have handsome amount of data. The main purpose of feature selection techniques is to select the important features to improve the classification accuracy and reduced the classification time. In this article, we proposed an hybrid features optimization technique named Whale Optimization Algorithm controlled Entropy (WOAcE).

Whale Optimization is new stochastic algorithm, implements population of search agents to find worldwide best solution to optimize the given problem. Whale optimization (WOA) is a metaheuristic developed by Mirjalili et al. [33] that replicates the hunting activity of humpback whales. The WOA optimization technique begins with the randomized populations being initialized. The search is separated into three stages: seeking for prey, encircling object and spiral bubble-net eating approach.

1) **SEEKING FOR PREY**

Whales seek for the target at randomly based on their current location. This humpback whale trait is employed to enhance the algorithm exploring potential. The behavior can be expressed numerically as follows:

\[
\tilde{A} = |S, p^{(n)}_\text{rn} - p^{(n)}| \\
\]

\[
p^{(n+1)} = p^{(n)}_\text{best} - B \tilde{A} \\
\]

where, the position vector is indicated by \( P \), randomly chosen vector from current population is \( P_{\text{rn}} \), contemporary iteration represented with \( n \), \( \tilde{A} \) shows the distance among present and a randomized member of population element by element multiplication is denoted by dot ( ) operator, and \( | | \) defines absolute value. The coefficient vectors \( B \) and \( S \) can be computed as follows:

\[
B = 2c_1 \times \text{rnd} - c_1 \\
S = 2 \times \text{rnd} \\
\]

During the iteration process, the linearly decreased number between 2 to 0 is represented by \( c_1 \) and \( \text{rnd} \) is the random number.

2) **ENCIRCLING PREY**

In this part, the best outcome presumed to be optimum solution. Leftover members of the population upgrade their places in relation to the current finest solution.

\[
\tilde{A} = |S, p^{(n)}_\text{best} - p^{(n)}| \\
\]

\[
p^{(n+1)} = p^{(n)}_\text{best} - B \tilde{A} \\
\]

where, the current best solution is represented by \( P_{\text{best}} \).

3) **BUBBLE-NET ATTACKING STRATEGY**

Humpback whales travel in helical structure pattern in response to a bubble-net attack. Mathematically, the bubble-net attacking method is defined as:

\[
A^* = p^{(n)}_\text{best} - p^{(n)} \\
\]

\[
p^{(n+1)} = A^* \cdot y^{bl} \cdot \cos(2\pi l) + p^{(n)}_\text{best} \\
\]

The shape of the logarithmic spiral is defined by \( b \) having constant value whereas a random number \( l \) is being calculated by the following equation:

\[
l = (c_2 - 1) \cdot \text{rnd} + 1 \\
\]
shifts among encircling prey and a bubble-net assault technique. Mathematically, it is formulated as follows:

\[ P^{n+1} = P^n_{\text{best}} - B \tilde{A} \quad \text{if } \beta < 0.5 \]  
\[ P^{n+1} = A^* y^{bl} \cos(2\pi l) + P^n_{\text{best}} \quad \text{if } \beta \geq 0.5 \]

where, \( P^{n+1} \) is the best optimum solutions and threshold value is 0.5. This choice of this value is not suitable way; therefore, we improve this equation by employing entropy formulation. Entropy value is computed as follows:

\[ H[F] = -\sum_{i=1}^{n} \tilde{P}(f_i) \log \tilde{P}(f_i) \]

where, \( f_i \) \( \in \) \( P^{n+1} \), \( H[F] \) is entropy value, and \( \tilde{P} \) is probability value of each feature. The main purpose of entropy value is to obtain the average bits of features needs to guess it elements successfully. Hence, the Eq. (22) is modified as follows:

\[ P^{n+1} = A^* y^{bl} \cos(2\pi l) + P^n_{\text{best}} \quad \text{if } \beta \geq H \]

Based on this equation, a resultant vector is obtained of dimensional \( N \times 422 \) that finally passed to neural network for final classification.

**IV. RESULTS AND DISCUSSION**

The proposed deep learning and improved optimization algorithm for citrus fruit diseases recognition is evaluated on three publically available datasets- Citrus fruits, Citrus leaf, and Hybrid. The detail of datasets is described under section 3.1. For the training of entire framework, 50% samples are utilized whereas the rest of 50% utilized for the classification purpose. The entire framework results are computed using 10-Fold cross validation. For the final classification, neural network is opted as a main classifier and compare performance with several other classifiers such as fine tree, coarse tree, Gaussian Naïve Bayes, linear SVM, quadratic SVM, and extreme learning machine (ELM). The performance of each classifier is computed based on two importance measures such as accuracy and classification time in seconds. The entire experimental process was conducted on MATLAB2021b using Work Station having 16GB RAM, 8 GB graphics card, and 500GB SSD.

**A. NUMERICAL RESULTS**

1) CITRUS FRUITS DATASET RESULTS

The proposed framework results in terms of tabular and visual forms are described in this section. The middle steps results in terms of numerical values are given in Table 2. In this table, the results of modified MobileNetV2, original whale optimization algorithm, and whale optimization with static threshold value are given for all selected classifiers. Neural network obtained better accuracy of 98.6% for Whale-Threshold optimization algorithm. The rest of the classifiers obtained best accuracy of 87.4, 78.9, 96.8, 97.8, 97.1, 98.1, and 97.8%, respectively. Based on the results given in this table, it is analyzed that the accuracy obtained for modified MobileNet (MobV2) is less than the accuracy got from whale optimization and Whale-Threshold algorithms. Moreover, it is also noted that the Whale-Threshold algorithm obtained better accuracy. Computational time during the classification process is also noted and, as given in Table 2. This table clearly indicated that the computational time of Whale-Threshold is minimum than the other steps. The minimum noted time is 29.77 (sec) of neural network using Whale-Threshold optimization algorithm.

| Classifier       | Features        | Measures          |
|------------------|-----------------|-------------------|
|                  | MobV2           | Whale Optimization| Whale-Threshold  | Accuracy (%) | Time (Sec) |
| Fine Tree        | ✅              | ✗                 | 82.6             | 115.67       |
| Coarse Tree      | ✗              | ✅                 | 87.4             | 41.66        |
| Gaussian Naïve Bayes |               | ✗                 | 74.7             | 121.89       |
| Linear SVM       | ✗              | ✗                 | 76.2             | 63.67        |
| Quadratic SVM    | ✗              | ✗                 | 78.9             | 45.06        |
| Cubic SVM        | ✗              | ✗                 | 91.5             | 117.34       |
| ELM              | ✗              | ✗                 | 94.6             | 67.44        |
| Neural Network   | ✗              | ✗                 | 96.8             | 49.54        |
|                  | ✗              | ✗                 | 94.6             | 82.66        |
|                  | ✗              | ✗                 | 97.8             | 78.44        |
|                  | ✗              | ✗                 | 92.5             | 183.90       |
|                  | ✗              | ✗                 | 92.5             | 183.90       |
|                  | ✗              | ✗                 | 92.5             | 183.90       |
|                  | ✗              | ✗                 | 92.5             | 183.90       |
|                  | ✗              | ✗                 | 92.5             | 183.90       |

*Note: The accuracy and time are given for the classification process.*
TABLE 3. Proposed method classification results on citrus fruits dataset.

| Classifier     | TPR (%) | Precision (%) | F1 Score (%) | FPR | AUC | ACC (%) | Time (Sec) |
|----------------|---------|---------------|--------------|-----|-----|---------|------------|
| Fine Tree      | 89.70   | 89.90         | 89.80        | 0.026 | 0.97 | 90.3    | 24.56      |
| Coarse Tree    | 80.10   | 81.14         | 80.62        | 0.048 | 0.93 | 81.4    | 26.99      |
| Gaussian Naive Bayes | 98.38 | 98.12         | 98.25        | 0.004 | 0.99 | 98.3    | 23.39      |
| Linear SVM     | 99.22   | 99.12         | 99.17        | 0.002 | 1.00 | 99.2    | 60.24      |
| Quadratic SVM  | 99.24   | 99.16         | 99.20        | 0.002 | 1.00 | 99.2    | 68.64      |
| Cubic SVM      | 99.26   | 99.20         | 99.23        | 0.002 | 1.00 | 99.3    | 72.50      |
| ELM            | 99.24   | 99.16         | 99.20        | 0.002 | 0.99 | 99.2    | 76.46      |
| Neural Network | 99.36   | 99.36         | 99.36        | 0.000 | 1.00 | 99.4    | 21.25      |

FIGURE 7. Confusion matrix of neural network for citrus fruits dataset.

2) CITRUS LEAF DATASET RESULTS

The results of citrus leaf dataset have been presented in Table 4. This table presents the middle steps results in terms of accuracy and computational time. Similar to Table 2, in this table, the results of modified MobileNetV2, original whale optimization algorithm, and whale optimization with static threshold value are given for all selected classifiers. Several classifiers are utilized and neural network obtained better accuracy of 97.7% for Whale-Threshold optimization algorithm. The rest of the classifiers obtained best accuracy of 83.6%, 75.2%, 59.0%, 93.5%, 92.5%, 96.8%, and 96.2%, respectively. The accuracy is not better for the originally extracted deep features from MobV2 but the accuracy is improved after the best features selection through original whale optimization algorithm and Whale-Threshold algorithm. Moreover, it is also noted that the Whale-Threshold algorithm obtained better accuracy than the original Mob2 and Whale-Threshold. Computational time during the classification process is also noted and, as given in Table 4. The time noted in this classifier clearly indicated that the computational time of Whale-Threshold algorithm is minimum than the other two steps. The minimum noted time in this table is 22.20 (sec) of neural network classifier.

Table 5 presents the entire proposed framework accuracy on Citrus Leaf Dataset. In this table, the best achieved noted accuracy is 99.4%, whereas the true positive rate (TPR) is 99.38, precision rate is 99.38, and F1-Score is 99.38%, respectively. The other classifiers also given the improved accuracy than the results mentioned in Table 4. The accuracy of neural network is further confirmed by a confusion matrix, illustrated in Figure 8. This figure demonstrated that the correct prediction rate of each class is 98.9%, 100%, 98.2%, 99.8%, and 100%, respectively. The computational time of each classifier is also noted for the entire proposed framework, and it is observed that the time is significantly reduced than the middle steps, as stated in Table 4. Hence, overall, the proposed framework is performed better on Citrus Leaf Dataset in terms of accuracy and classification computational time.
3) CITRUS HYBRID DATASET RESULTS

Table 6 presents the results of hybrid citrus dataset using middle steps of proposed framework. The results are presented in the form of accuracy and computational time. In this table, the results of modified MobileNetV2, original whale optimization algorithm, and whale optimization with static threshold value are given for all selected classifiers. Neural network obtained the highest accuracy of 98.5% for Whale-Threshold optimization algorithm. The rest of the classifiers obtained the best accuracy of 85.2, 75.2, 66.5, 96.3, 97.0, 97.8, and 98.0%, respectively. Based on the accuracy and time given in this table, it is clearly observed that accuracy is improved after the whale optimization algorithm that is further improved through Whale-Threshold algorithm. Moreover, it is also noted that the Whale-Threshold algorithm obtained better accuracy than the original MobV2 and Whale-Threshold. Computational time during the classification process is also noted and, as given in Table 6. The time noted in this classifier clearly indicated that the computational time of Whale-Threshold algorithm is minimum than the other two steps. The minimum noted time in this table is 17.09 (sec) of neural network classifier.

Table 7 presents the entire proposed framework results for Hybrid Citrus Dataset. The best achieved noted accuracy is 99.7%, whereas the true positive rate (TPR) is 99.7, precision rate is 99.6, and F1-Score is 99.30%, respectively. The rest of the classifiers also gave the improved accuracy than the classification results mentioned in Table 4. Figure 9 illustrated the confusion matrix of neural network to verify the achieved accuracy of neural network. This figure demonstrated that the correct prediction rate of each class is 99.4, 100, 99.3, 100, 100, and 99.3%, respectively. The computational time of each classifier is also noted for the entire proposed framework, and it is observed that the time is significantly reduced than the middle steps, as stated in Table 6. Hence, overall, the proposed framework is performed better on Hybrid Citrus Dataset in terms of accuracy and classification computational time.

B. DISCUSSION

A brief discussion has been added in this section for proposed framework of citrus fruit diseases classification. The
TABLE 7. Proposed classification results using hybrid citrus fruit and leaf diseases dataset.

| Classifier            | TPR (%) | Precision (%) | F1 Score (%) | FPR | AUC   | ACC (%) | Time (Sec) |
|-----------------------|---------|---------------|--------------|-----|-------|---------|------------|
| Fine Tree             | 86.6    | 86.8          | 86.70        | 0.03| 0.958 | 87.4    | 13.59      |
| Coarse Tree           | 77.6    | 78.6          | 78.10        | 0.05| 0.926 | 78.9    | 15.19      |
| Gaussian Naive Bayes  | 68.2    | 68.2          | 68.20        | 0.08| 0.83  | 69.3    | 13.86      |
| Linear SVM            | 98.8    | 98.8          | 98.80        | 0.002| 1.00  | 99.0    | 14.12      |
| Quadratic SVM         | 99.0    | 99.2          | 99.09        | 0.002| 1.00  | 99.1    | 23.08      |
| Cubic SVM             | 99.0    | 99.2          | 99.09        | 0.00 | 1.00  | 99.3    | 18.05      |
| ELM                   | 99.4    | 99.2          | 99.29        | 0.002| 1.00  | 99.4    | 18.92      |
| Neural Network        | 99.7    | 99.6          | 99.30        | 0.00 | 1.00  | 99.7    | 10.70      |

FIGURE 9. Confusion matrix of neural network for hybrid citrus fruit and leaf diseases dataset.

architecture of proposed framework is illustrated in Figure 1. In this figure, it is shown that the data augmentation is performed at the initial step to increase the size of dataset that further improved the classification accuracy, as presented in Figure 10. In this figure, it is noted that the accuracy on original datasets is 92.5, 92.8, and 93.1%, respectively. After the data augmentation, the accuracy is significantly improved of 99.4, 99.4, and 99.7%, respectively. After data augmentation, features are extracted from deep learning models and performed optimization. The results are given in Tables 2-7. Based on these tables, it is clearly shown that the proposed framework obtained higher accuracy. At the end, a brief comparison is also conducted with some recent techniques, as presented in Table 8. In this table, it is noted that the recent best accuracy was 95.5%. In this work, the obtained accuracy is 99.4, 99.4, and 99.7%, respectively on selected datasets which is improved than the previous techniques.

V. CONCLUSION

In this research work, single stream convolutional neural network and improved optimization architecture is proposed for citrus fruit diseases classification. Proposed architecture includes few important steps. Data augmentation is performed initially to grow number of training samples based on four contrast enhancement operations- shadow removal, adjusting pixel intensity, improving brightness, and improving local contrast. Key purpose of this step is better training of selected CNN model. A pre-trained MobileNet-V2 CNN model is opted and modified initially and then trained on newly augmented dataset by employing transfer learning concept. From newly trained model Deep features are extracted. Based on the analysis of extracted deep features, it is analyzed that the extracted features also include some redundant information. Thus, an improved Whale Optimization Algorithm is proposed. Improved optimization algorithm selects features in two-way check process. Lastly, best selected features are classified using neural network for final classification results. The experimental procedure was conducted on augmented citrus fruits, leaves, and hybrid dataset and reached an accuracy of 99.4, 99.5 and 99.7%. Comparing with existing methods, the proposed architecture performed better performance.
in terms of accuracy and time. From results, the major findings are: i) Increases in training data improve the learning capability of a CNN model that later gives better recognition accuracy; ii) selection of best features process maintain accuracy but significantly reduces computational time. In future work, duo-stream architecture shall be opted and evaluated on more complex datasets.

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MUHAMMAD ATTIQUE KHAN (Member, IEEE) received the master’s and Ph.D. degrees in human activity recognition for application of video surveillance and skin lesion classification using deep learning from COMSATS University Islamabad, Pakistan. He is currently a Lecturer with the Computer Science Department, HITEC University, Taxila, Pakistan. He has above 190 publications that have more than 6500 citations and impact factor more than 600 with H-index 50. His research interests include medical imaging, COVID19, MRI analysis, video surveillance, human gait recognition, and agriculture plants. He is a Reviewer of several reputed journals, such as the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, the IEEE TRANSACTIONS ON NEURAL NETWORKS, PATTERN RECOGNITION LETTERS, MULTIMEDIA TOOLS AND APPLICATION, COMPUTERS AND ELECTRONICS IN AGRICULTURE, IET IMAGE PROCESSING, BIOMEDICAL SIGNAL PROCESSING CONTROL, IET COMPUTER VISION, EURASIP JOURNAL OF IMAGE AND VIDEO PROCESSING, IEEE ACCESS, SENSORS (MDPI), ELECTRONICS (MDPI), APPLIED SCIENCES (MDPI), DIAGNOSTICS (MDPI), and CANCERS (MDPI).

AMMAR ARMGHAN was born in Faisalabad, Pakistan, in February 1984. He received the B.S. degree in electrical engineering from COMSATS University, in 2006, the M.S. degree in electronics and communication engineering from the University of Nottingham, in 2010, and the Ph.D. degree from the Wuhan National Laboratory of Optoelectronic, Huazhong University of Science and Technology, Wuhan, China, in 2016. In 2006, he joined the School of Electrical Engineering, The University of Faisalabad, as a Lecturer. He is currently working as an Assistant Professor at Jouf University, Saudi Arabia. His research interest includes complementary metamaterial-based microwave and terahertz devices.

SARA A. ALTHUBITI received the Ph.D. degree in computer science from North Carolina A&T State University, USA. She is currently an Assistant Professor at the College of Computer and Information Sciences, Majmmah University, Saudi Arabia. Her research interests include machine learning, deep learning algorithms with applicability of different domains, pattern recognition, and intrusion detection.

MAJED ALHAISONI is currently a Professor of computer science at the College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia. He has published more than 50 high-impact factor articles in last three years. His research interest includes artificial intelligence and optimization. He is also a Reviewer of many journals, such as Multimedia Systems, Multimedia Tools and Applications, and the IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE.

ABDULLAH ALQAHTANI received the bachelor’s degree in computer science from King Saud University, Saudi Arabia, in 2007, and the master’s and Ph.D. degrees in advanced computer science from the University of Leicester, U.K., in 2011 and 2020, respectively. He is currently an Assistant Professor of computer science with Prince Sattam Bin Abdulaziz University. His research interests include model-driven development, big data processing and analytics, and graph transformation theory and its applications in machine learning and AI.

SEIFEDINE KADRY (Senior Member, IEEE) received the bachelor’s degree from Lebanese University, in 1999, the M.S. degree from the University of Reims, France, and the EPFL, Lausanne, in 2002, the Ph.D. degree from Blaise Pascal University, France, in 2007, and the H.D.R. degree from the University of Rouen Normandy, in 2017. He is currently a Full Professor of data science with the Noroff University College, Norway. He is also an ABET Program Evaluator of computing and an ABET Program Evaluator of engineering technology. His current research interests include data science, education using technology, system prognostics, stochastic systems, and probability and reliability analysis.

YONGSUNG KIM received the M.S. and Ph.D. degrees in computer engineering in Korea University, Seoul, South Korea, in 2013 and 2018, respectively. From 2020 to 2021, he was with the Department of Software Engineering, Cyber University of Korea, Seoul. He is currently a member of the Faculty at the Department of Technology Education, Chungnam National University, Daejeon, South Korea. His current research interests include machine learning, deep learning, semantic web, and educational data mining.

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