A CONV-EGBDNN Model for the Classification and Detection of Mango Diseases on Diseased Mango Images utilizing Transfer Learning

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ABSTRACT

Mango fruits are highly valued for their taste, flavor, and nutritional value, making them a popular choice among consumers. However, mango fruits are susceptible to various diseases that can significantly affect their yield and quality. Therefore, accurate and timely detection of these diseases is crucial for effective disease management and minimizing losses in mango production. Computer-aided diagnosis techniques have emerged as a promising tool for disease detection and classification in mango fruits. This study adopts an image classification approach to identify various diseases in mangos and distinguish them from healthy specimens. The pre-processing phase involves a Wiener filter for noise removal, followed by Otsu's threshold-based segmentation as a crucial operation. Subsequently, features are extracted by implementing the ResNet50 model. The proposed model was experimentally verified and validated, demonstrating optimal results with an accuracy of 98.25%. This high accuracy rate highlights the effectiveness of the XG-Boost classifier in accurately categorizing mango images into different disease categories. The experimental results strongly support the potential practical application of the model in the agricultural industry for disease detection in mango crops.

Keywords-deep learning; mango fruit; XG-Boost; transfer learning; ResNet50

I.   INTRODUCTION

Mangos are widely considered one of the most delicious and nutritious fruits. Not only are they a rich source of vitamins A, C, and D, but they also contain various essential minerals and antioxidants. According to [1], mangos are examined based on human eye examination, which is often insufficient. This traditional approach to classifying mangos can be time-consuming and subjective, making it difficult for food processing industries to accurately determine the ripeness and quality of mangos for commercial purposes. As a result, there has been an increasing interest in the development of automated classification systems for mangos using computer-aided diagnosis techniques. These techniques utilize advanced technologies, such as Machine Learning (ML), Deep Learning (DL), and computer vision to accurately detect and classify mango fruits based on their external features, weight, and other quality attributes [2]. By employing computer-aided diagnosis techniques, the detection and classification of diseases in mango fruits can be significantly improved. These techniques

allow early identification of diseases, such as anthracnose [3], powdery mildew, and bacterial black spots, which can greatly affect the yield and quality of mango crops. In addition, computer-aided diagnosis techniques provide a non-destructive and efficient approach to monitoring and mitigating the spread of diseases in mango orchards. This study aimed to explore the importance of classification and disease detection in mango fruits using computer-aided diagnosis techniques. To accomplish this, various methodologies and technologies used in the field of mango fruit disease detection and classification were examined [4]. Pre-trained deep neural network models have played a significant role in mango fruit detection and classification tasks. Models, such as Mask R-CNN, AlexNet, VGGs, and ResNets have been utilized to take advantage of their learned features and hierarchical representations in computer vision tasks [5]. By employing transfer learning, these pre-trained models can be finetuned and adapted to the specific task of mango fruit detection and classification. This significantly reduces the need for large annotated datasets and computational resources, as the pre-trained models already

have learned representations of various visual features [6]. Additionally, the use of pre-trained models allows for faster model convergence and improved accuracy, as the models have already been trained on large-scale datasets like ImageNet. Pre-trained DNN models serve as powerful tools in mango fruit detection and classification tasks by providing a foundation of knowledge and learning features that can be applied to accurately identify and classify mango fruits based on their appearance [7]. These pre-trained models have shown promising results in accurately detecting diseases, involving anthracnose, powdery mildew, and bacterial black spots in mango fruits. Their ability to extract meaningful features from images enables models to identify subtle variations in texture, shape, and color that indicate specific diseases. The use of pre-trained DNN models in mango fruit detection and classification tasks not only improves the accuracy and efficiency of disease identification, but also allows researchers and farmers to make informed decisions on disease management and prevention strategies [8].

This study proposes the CONV-EGBDNN model to automatically identify and categorize diseases in mango fruits. The procedure starts with pre-processing, where a Wiener filter is used to enhance image quality. Following this pre-processing step, Otsu's threshold-based segmentation is employed for the segmentation procedure. Subsequently, feature extraction is carried out utilizing a pre-trained ResNet50 neural network. The extracted characteristics are then input into the Extreme Gradient Boosting (XG-Boost) classification model to distinguish between various conditions in mango fruits. A thorough examination of the experimental results reveals that the CONV-EGBDNN model outperforms the current methods, demonstrating superior performance in the recognition and classification of mango fruit diseases.

II.   RELATED WORKS

The diagnosis of fruit identification diseases involves examining its color and texture. Notably, a considerable amount of fruit studies concentrate on tree-based fruits, while this study specifically looks into techniques for categorizing fruit types. In [9], an input image was acquired through a webcam, saved as a JPEG file format, and underwent 11 preliminary processing steps. The detection of ripe or unripe mangos was achieved by analyzing color features derived from mango images, which were then classified. In [10], digital cameras were engaged to capture images, aiming to enhance the quality of the image data input. Several pre-processing procedures, including resizing and image enhancement, were carried out to identify the region of interest. Within a 5-second timeframe, the system successfully detected mango diseases utilizing textural feature extraction. Finally, the classification was executed using SVM. In [11], two cameras were implemented to capture mango fruit images of varying colors and sizes, which were then resized, grayscaled, and binary converted. Various segmentation techniques were then deployed, including edge-based algorithms, clustering approaches, region-based methods, and split/merge techniques. The extraction of hybrid characteristics, such as shape and color features, from mango images ensued, and finally, mango images were classified. 500 pictures of each leaf, fruit, and flower were taken with a resolution of 4320×3240 pixels, capturing both healthy and diseased parts using a digital camera. In [12], pre-processing steps, such as edge enhancement, gamma correction, and segmentation, were applied. Utilizing a blend of wavelet-PCA-based statistical features and modified rotation kernel transformation-based directional features, certain characteristics were extracted from mango leaves, flowers, and fruits to identify pathological issues in mango plants. The identification of pathological problems in mangos was carried out successfully through the combined feature extraction process. In [13], the identification of black spot disease in mango fruits was executed using an Artificial Neural Network (ANN). In [14], images capturing external bacteria disease on Alphonso mangoes were transformed into a binary format before undergoing various pre-processing procedures, such as histogram computations and segmentation. Color characteristics were extracted to differentiate between healthy and infected mangoe. Ultimately, the identification of bacterial diseases in mango fruits was performed. In [15], a least-squares SVM method based on fractal analysis and CIELab parameters was followed to detect browning on mangos.

III.   PROPOSED CONV-EGBDNN APPROACH

Figure 1 depicts a detailed workflow of the CONV-EGBDNN. First, a Wiener filter is applied to eliminate noise and improve the image quality. Next, Otsu's threshold segmentation is implemented for the segmentation step. After that, the extraction of features is carried out engaging the ResNet50 model, and finally, the XG-Boost method is applied for image classification by assigning specific class labels.
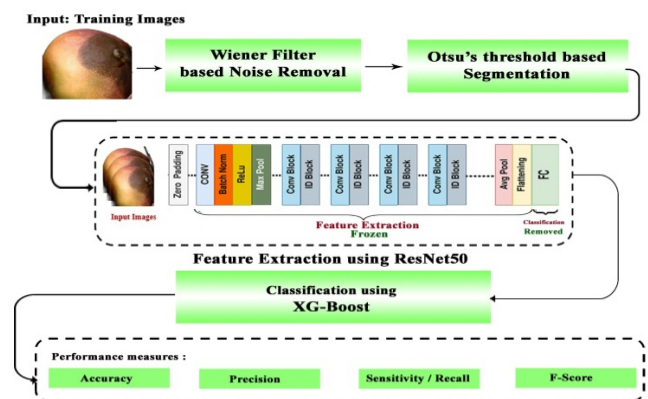

Fig. 1.   The architecture of the proposed CONV-EGBDNN model.

A. Wiener Filter-based Noise Removal

The Wiener filter acts as a traditional method in signal processing to eliminate noise from images. When dealing with the identification and diagnosis of diseases in mango fruit images, the Wiener filter can be deployed to enhance image quality by minimizing noise, thereby boosting the accuracy of disease identification algorithms. The formula for the Wiener filter in the spatial domain is given by:

$$\hat{f}(x,y) = H(u,v)F(u,v) + N(u,v) \qquad (1)$$

where $\hat{f}(x,y)$ is the estimate of the original image, $H(u,v)$ is the Wiener filter transfer function, $F(u,v)$ is the Fourier transform of the noisy image, and $N(u,v)$ is the Fourier transform of the noise. The Wiener filter transfer function $H(u,v)$ is defined as:

$$H(u,v) = \frac{G(u,v)}{G(u,v)+\frac{1}{S(u,v)}} \qquad (2)$$

where $G(u,v)$ is the Power Spectral Density (PSD) of the original image, and $S(u,v)$ is the PSD of the noise. Based on the concept of minimizing the mean square error between the initial image and the filtered one, the Wiener filter works by estimating the power spectral density of both noise and signal [16]. Subsequently, the former applies a filter that strikes a balance between noise reduction and preservation of signal characteristics, as observed in Figure 2. Through the application of the Wiener filter to mango fruit images, noise levels can be significantly reduced, supporting precise disease recognition and diagnosis on mangos.
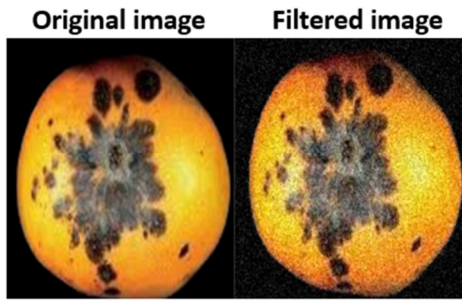

Fig. 2.   Wiener filter-based noise removed images.

B. Otsu's Threshold-based Segmentation

In the realm of mango fruit disease detection and classification through the utilization of images of infected fruits, Otsu's thresholding technique holds significant importance. The pre-processing of images using Otsu's thresholding can extract valuable features for classification and detection. Segmentation of the mango fruit images into distinct sections or elements is achievable by leveraging Otsu's thresholding, which is based on pixel intensity. This segmentation helps differentiate between diseased areas and healthy regions, facilitating easier analysis and classification of diseases.

Following the segmentation of the image, characteristics such as color, texture, and shape can be derived from the segmented areas. These characteristics offer essential insights into the attributes of the diseased regions, which are instrumental in the classification process. By isolating the diseased segments of the mango fruit images, Otsu's thresholding greatly improves the accuracy of disease classification. Focusing on the segmented regions with diseased attributes enables classification algorithms to effectively distinguish between various types of disease [17]. Moreover, Otsu's thresholding contributes to noise reduction in the images by separating the background from the foreground, as demonstrated in Figure 3. This separation improves image quality and refines the precision of disease detection and

classification algorithms. First, it calculates the histogram $H(i)$ of the input image, where i represents pixel intensity values ranging from 0 to L-1 (assuming L gray levels). Then, it normalizes the histogram to obtain the probability density function $p(i)$, representing the probability of occurrence of each pixel intensity as:

$$p(i) = \frac{H(i)}{N} \qquad (3)$$

where N is the total number of pixels in the image. The Cumulative Distribution Function (CDF) $P(i)$ is defined as:

$$P(i) = \sum_{k=0}^{i} p(k) \qquad (4)$$

The global mean intensity μ_T of the image is calculated by:

$$\mu_T = \sum_{i=0}^{L-1} i \cdot p(i) \qquad (5)$$

The inter-class variance is calculated as:

$$\sigma_B^2(t) = \frac{[P(t)(\mu(t)-\mu_T)]^2}{[P(t)(1-P(t))]} \qquad (6)$$

where t is the threshold value, $\mu(t)$ is the mean intensity of the pixels below threshold t, and $P(t)$ is the probability of the pixels below threshold t. The optimal threshold t_{opt} is determined by maximizing the inter-class variance:

$$\sigma_B^2(t) \; t_{opt} = \; arg \, max_t \; \sigma_B^2(t) \qquad (7)$$
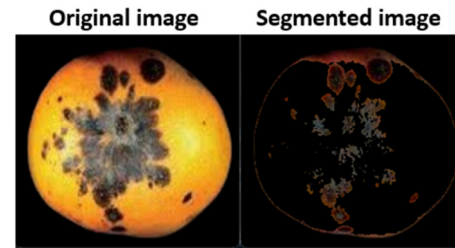

Fig. 3.   Otsu's threshold-based segmented image.

C. Feature Extraction Using ResNet50

ResNet50 stands as a Convolutional Neural Network (CNN) architecture widely used for image classification assignments. It is a key part of the Residual Network (ResNet) lineage, recognized for effectively training very deep neural networks through the utilization of residual connections. Pre-trained on the extensive ImageNet dataset, ResNet50 holds millions of images spanning numerous categories. Through the feature extraction process, ResNet50 adeptly captures high-level attributes from images. Ahead of inputting images for feature extraction into ResNet50, pre-processing steps are commonly carried out to guarantee alignment with the network's input requisites. Typically, this involves altering the images to a standard size and standardizing the pixel values. The loading of ResNet50 as a pre-trained model is usually performed deploying deep learning frameworks, such as TensorFlow, PyTorch, or Keras. These frameworks offer APIs for the effortless loading of the pre-trained ResNet50 model with its ImageNet dataset-trained weights. After loading the pre-trained ResNet50 model, the former is used to derive features from the input images. In the feature extraction mode,

the network's classifier layers are eliminated, leaving only the convolutional layers, as spotted in Figure 4. These convolutional layers function as feature exchangers, capturing high-level visual attributes from the input images. By forwarding the images through the pre-trained ResNet50 model, the convolutional layers hierarchically process the images, extracting attributes at varied spatial resolutions and semantic levels. The ultimate output of the last convolutional layer mirrors the high-level features drawn from the input images.

The deduced features provided by ResNet50 can be applied as feature representations of the input images. These feature representations generally encompass high-dimensional vectors that encode the extracted visual data [18]. Occasionally, the high-dimensional feature representations extracted by ResNet50 may outweigh specific downstream requirements. Techniques for dimensionality reduction, such as Principal Component Analysis (PCA), can be adopted to attenuate the dimensionality of the feature vectors while retaining most of the significant information. The derived features can be used as input for diverse downstream tasks, involving image classification, object detection, image retrieval, or transfer learning. In an instance related to the detection and classification of mango fruit diseases, these features can be fed into XG-Boost to categorize mango fruits into varied disease types, based on the extracted visual features.
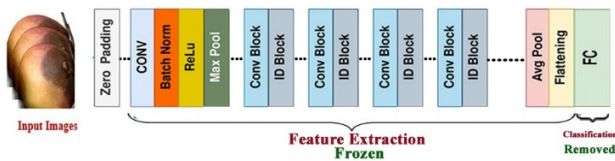

Fig. 4.   ResNet50 as a feature extractor.

D. Classification Using Extreme Gradient Boosting (XG-Boost)

XG-Boost stands out as a popular algorithm in the realm of ML due to its notable efficiency and performance in classification activities. When it comes to identifying diseases in mango fruits through images, XG-Boost can be applied to grasp patterns from image characteristics and precisely categorize the aforementioned fruits into diverse disease categories [19]. XG-Boost can extract pertinent characteristics from mango fruit images including color histograms, texture details, shape aspects, and more. Let us symbolize the feature array of an image i as X_i. Then, let us allocate designations to the images to specify the disease category each image is linked with. As an illustration, when there are five disease categories, assign a designation y_i to each image specifying the disease category it aligns with, which could be conveyed as $y_i = 0, 1, 2, 3, 4$. XGBoost focuses on reducing a standardized objective function, which comprises a summation of a loss function and a regulating term. Regarding multiclass categorization, the softmax loss function is a prevalent choice for the loss function. The objective function can be formulated as:

$$obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \qquad (8)$$

where n is the number of training examples, $L(y_i, \hat{y}_i)$ is the softmax loss function that measures the difference between the true label y_i and the predicted probabilities $\hat{y}_i$ across all classes, K is the number of trees (weak learners) in the model, f_k is the k-th decision tree, and $\Omega(f_k)$ is the regulation term penalizing the complexity of the model.

XGBoost constructs a series of decision trees in sequence. Each round involves adding a new tree to address the mistakes made by the current trees. The ensemble's prediction result from summing up the individual trees' predictions is:

$$\hat{y}_i = softmax\left(\sum_{k=1}^{K} f_k(X_i)\right) \qquad (9)$$

where $f_k(X_i)$ is the prediction of the k-th tree for the input features X_i and the softmax function converts the raw outputs into probabilities. XGBoost improves the objective function by sequentially introducing new trees that minimize the softmax loss. The training process halts either when a set number of trees is reached or when further splits no longer notably improve the objective function. Training an XGBoost classifier on a selection of mango fruit photos paired with labels for five different disease categories allows the model to effectively distinguish between various mango fruit diseases based on their visual characteristics, enhancing the precision of detection and classification.

IV.   EXPERIMENTAL RESULTS

A. Implementation Setup

Validation experiments were carried out to evaluate the effectiveness of the CONV-EGBDNN approach in identifying and categorizing mango fruit diseases through images of infected fruits considering various elements. Testing was carried out using Python 3.6.5 on a PC featuring an i5-8600K processor, 250 GB SSD, GeForce 1050Ti 4 GB GPU, 16 GB RAM, and a 1 TB HDD. The performance evaluation of the CONV-EGBDNN model included the examination of essential metrics, such as sensitivity, specificity, precision, accuracy, and F-score. The evaluation process was executed on a recognized Kaggle dataset that included images of diseased mango fruits [20]. Figure 5 manifests specific examples of test images for each classification, and Table I details the corresponding sample quantities.

Fig. 5.   Sample dataset images.

TABLE I.   DATASET DESCRIPTION

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

B. Observations and Discussions

Figure 6 presents the confusion matrix of the CONV-EGBDNN model for various classes in detecting and categorizing mango fruit diseases. Table II and Figure 7 provide the efficiency evaluation of the CONV-EGBDNN model, highlighting its effectiveness in identifying mango fruit diseases in both training and testing datasets. A training-to-testing split of 70% to 30% was applied. The model exhibited exceptional performance in recognizing mango fruit diseases, achieving higher performance metrics, such as an F-score of 97.00%, an impressive overall accuracy of 98.25%, a sensitivity of 97.00%, and a precision of 97.00%.

Table III presents the superior performance of the proposed CONV-EGBDNN model through a detailed comparison analysis. This table provides a concise evaluation of accuracy and other parameters for the CONV-EGBDNN model compared to the models presented in [21]. The accuracy values of the models in [21] were the lowest, measuring 95.00%, 82.00%, 86.00%, and 97.00% respectively, whereas the proposed model outperformed them with a score of 98.25%. The sensitivity values of the models in [21] showed lower percentages between 82.00% and 94.03%, whereas the proposed model outperformed them with a score of 97.00%. The precision values of the models in [21] were notably minimal, ranging from 92.00% and 95.00%, whereas the proposed model excelled with a precision of 97.00%. Additionally, the models in [21] had lower F-score values, ranging from 68.00% to 94.02%. In contrast, the proposed CONV-EGBDNN model demonstrated excellent performance with an F-score of 97.00%. Figure 8 entails a visual representation comparing the proposed model with the existing models.

TABLE II.   RESULTS OF CONV-EGBDNN FOR MANGO FRUIT DISEASE CLASSIFICATION

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F-Score (%)
CONV-EGBDNN	98.25	97.00	97.00	97.00

Fig. 6.   (a) Confusion matrix based on the TR set, (b) Confusion matrix based on the TS set (c), Precision-Recall curve, (d) ROC curve.

TABLE III.   COMPARISON OF THE PROPOSED WITH EXISTING MODELS

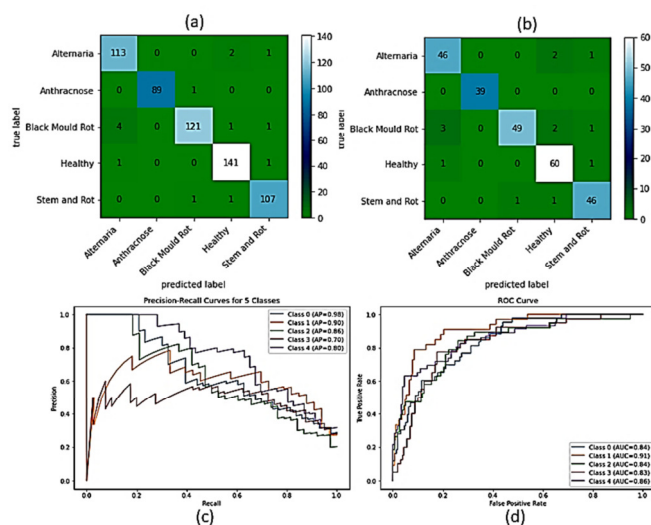| Models	Accuracy (%)	Sensitivity (%)	Precision (%)	F- Score (%)
CNN-HOG	95.00	82.00	92.00	68.00
CNN	82.00	79.00	93.00	63.00
L-CNN	86.00	69.00	78.00	57.00
CNN-FOA	97.00	94.03	95.00	94.02
CONV-EGBDNN	98.25	97.00	97.00	97.00

Fig. 7.   Accuracy and loss graphs based on training and testing set.
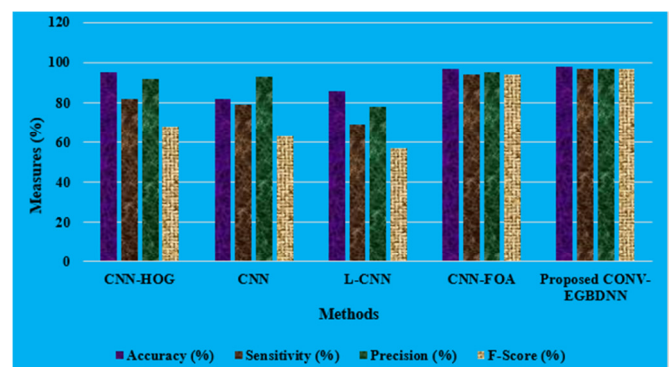

Fig. 8.   Comparative analysis of the proposed and existing models.

V.   CONCLUSION

The exceptional accuracy, recall, precision, and F-score of the CONV-EGBDNN model demonstrate its strength and dependability in handling the complexities of detecting mango fruit diseases. The model's ability to precisely categorize

diseases can result in early and accurate identification of affected mango fruits, facilitating prompt actions to curb disease spread and minimize losses in the crop yield. Furthermore, the proposed CONV-EGBDNN model is scalable and flexible, making it appropriate for use in various agricultural environments and geographical locations. Its effectiveness in classifying mango fruit diseases can improve agricultural management practices but also can display potential for wider applications in other sectors of agriculture, contributing to overall food sustainability and security. The incorporation of advanced computational techniques such as CNNs and ensemble methods like XG-Boost highlights the possibility of utilizing innovative methods to tackle agricultural problems. This interdisciplinary strategy encourages innovation in agricultural research and opens paths for developing unique solutions to intricate agricultural challenges. Future advancements for the proposed CONV-EGBDNN model involve enhancing dataset variety through data augmentation, exploring transfer learning for regional customization, investigating sensor integration for real-time disease detection in agricultural fields, and cooperating with stakeholders for validation and continual enhancement in real-world scenarios.

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