Automatic Detection and Classification of Mango Disease Using Convolutional Neural Network and Histogram Oriented Gradients

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Automatic Detection and Classification of Mango Disease Using Convolutional Neural Network and Histogram Oriented Gradients

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Abstract: This study suggests a Convolutional Neural Network (CNN) and Histogram Oriented Gradients (HOG)-based automatic detection and classification system for mango disease. Early detection is essential for efficient disease management since mango disease can have a major influence on fruit quality and yield. The suggested system makes use of the CNN algorithm for extracting features and the HOG technique for capturing shape and texture data. The extracted features are subsequently used to feed a disease classification model for disease detection. The efficiency of the proposed model is demonstrated by experimental findings, which achieve excellent accuracy in both disease detection and classification tasks. The CNN-HOG hybrid model outperforms CNN or HOG alone in terms of performance, demonstrating the complementary nature of these two methods for the detection and classification of mango disease. The system's performance is evaluated using measures for accuracy, precision, and recall and the accuracy of the proposed model is 98.80%. This research helps establish effective and trustworthy tools for managing mango disease by automating the detection and classification process. This enables prompt intervention and reduces crop losses.

Keywords: Automatic detection, classification, mango disease, Convolutional Neural network, Histogram oriented gradient, hybrid approach.

1 Introduction

In Ethiopia, 80% of the population relayed in the agricultural sectors. Even the country followed an agricultural-led industry policy to maintain food security (Abera et al., 2016). The mango fruit is not only the most delicious, but it has an impressive nutritional profile. Some of the important nutrition existed in mango fruit are Vitamin E, Protein, Calories, Vitamin C, Potassium, and Niacin which are very important for good health (Nickels & Croot, 2009). In terms of economic importance, the banana and mango are the two most extensively cultivated fruit crops in Ethiopia (Gutema & Tadesse, 2022). According to the, (CSA, 2007) Central Statistical Agency Report Mangoes are produced on 16,363.48 hectares of land, yielding a total of 105,379.375 tons. However, mangoes are susceptible to many diseases, which can cause significant crop losses. Early detection of these mango diseases is very important to avoid a severe decline in yield and agricultural production levels. Traditional methods of detecting and diagnosing diseases are labor-intensive and time-consuming and they can be inaccurate. This can lead to significant crop losses, as diseases can spread quickly and cause damage to mango trees.

The automatic detection and diagnosis system can improve the accuracy and efficiency of disease detection and diagnosis by enabling farmers to quickly and objectively assess the health status of mango trees. This helps farmers take timely action to prevent the spread of disease and protect their crops. Automated systems can also reduce the cost of disease management by reducing the need for manual inspections and providing farmers with more accurate information on disease severity. Finally, automated systems help make mango production more sustainable by reducing the use of pesticides and other polluting chemicals. Deep learning models offer a promising alternative for the automatic detection and diagnosis of mango diseases. Deep learning is highly effective in image classification, object detection, and natural language processing tasks (Goyal et al., 2019). In recent years, deep learning models have been used to automate the detection and diagnosis of various diseases including mango disease. The author(Wongsila et al., 2021) employed a CNN algorithm to develop a model for the detection of mango affected by anthracnose disease. The researcher uses 350 total image datasets to develop, train and test the model and gets an accuracy of 70%. The researcher uses a very small amount of data and the developed model is focused on identifying only Anthracnose Mango disease. Similarly, the researcher(Arivazhagan & Ligi, 2018) proposed a convolutional neural network (CNN) for the automatic detection and classification of mango leaf diseases. A dataset of 1200 images of mango leaves was used by the authors, 500 of which were of unharmed leaves and 700 of which were of leaves that had one of five different diseases (anthracnose, alternaria leaf spots, leaf gall, leaf Webber, and leaf burn). With the help of this dataset and a CNN that was trained on it, they were able to diagnose mango plant leaf disease with an accuracy of 96.67%. on the other hand (Tusher et al., 2022) propose a CNN-based technique for automatically identifying and categorizing plant leaf diseases. The researchers examined a dataset of 6000 photos of plant leaves, of which 2000 showed leaves in good health and 4000 showed leaves affected by 10 distinct diseases, including anthracnose, alternaria leaf spots, leaf gall, leaf webber, leaf burn, powdery mildew, rust, scab, and yellow spot. By using this dataset to train a CNN, they were able to identify plant illnesses that affect the leaves with a 95.4% accuracy rate. The author(Peters & Panayi, 2015) also develop a mango fruit defect detection system using CNN and computer vision. The researcher uses a limited number of mango fruit images to classify the quality of mango and the accuracy of the model is tested with a small amount of data.

This article presents a deep learning model for the automatic detection and diagnosis of mango diseases to maintain high accuracy and minimize false-negative situations. To improve the precision and effectiveness of the detection and classification of mango disease, our methodology incorporates a variety of image processing and deep learning techniques. To begin with, mango leaf images are segmented using threshold image segmentation, which successfully isolates the regions of interest related to the infection of mango disease. This method aids in defining the disease's affected areas, allowing for more accurate analysis and subsequent procedures. Anisotropic diffusion filtering (ADF) is used to reduce noise interference in the mango disease images. While keeping critical structures and features necessary for precise diagnosis, ADF successfully eliminates noise. To assess the usefulness of ADF in improving the quality of photographs of mango illness, its performance is compared with that of other filters. Convolutional Neural Networks (CNN) and Histogram Oriented Gradients (HOG) are used in a hybrid approach to extract useful characteristics from the segmented and filtered images of the mango disease. While HOG focuses on shape and texture information, CNN excels at capturing complex patterns and high-level representations. By combining these two strategies, feature extraction is improved, increasing the precision of subsequent analysis. The YOLOv3 (You Only Look Once version 3) technique is also used for object detection and makes sure that only pertinent photos are exposed to further analysis, decreasing computing overhead and improving system efficiency.

Finally, based on the extracted features, mango disease infection is classified using Support Vector Machines (SVM). Accurate classification results can be produced by using a tagged dataset of images of the mango disease to train the SVM model. The suggested methodology aims to provide an effective and dependable system for the analysis of mango disease images in the context of mango disease detection by integrating threshold image segmentation, anisotropic diffusion filtering, CNN-HOG feature extraction, YOLOv3 object detection, and SVM classification. This research helps the early detection and management of mango disease by increasing the accuracy and effectiveness of diagnosis, potentially resulting in improved detection and classification of mango

2 Related work

Machine learning and deep learning techniques have played an important role in agricultural sectors for the prediction, classification, and detection of plant disease and provide non-destructive, low-cost, fast, and reliable means of plant disease detection. Different researchers have researched the diagnosis and detection of plant disease specifically on mango disease. Some of the researchers are:

(Nithya et al., 2022) researched developing a computer vision system to detect mango defects using advanced machine learning techniques. The researcher uses a convolutional neural network (CNN) to develop the mango defect detection model. The researcher took 50 good and 50 defective mango datasets from an online repository and applied data preprocessing techniques to enhance the quality of the image, remove the noise from the image, and data augmentation techniques to enlarge the sample dataset. Histogram Equalization techniques to improve the contrast and quality of images and adaptive Wiener Filter to remove noise from the images. Finally, the researcher uses CNN to develop a computer vision-based mango defect detection model and got 89.5% accuracy in the results

(Sanath Rao et al., 2021) conducted research on the detection of grapes and mango disease detection by transfer learning and deep learning approaches. The researcher uses 8438 image datasets collected from the plant village dataset to detect and classify grapes and mango disease and the CNN is trained to identify the disease. Alex-Net is modeled for feature extraction and classification and the researcher uses MATLAB and gets an accuracy of 99% and 89% results for grapes and mango leaves respectively.

(Arya & Singh, 2019) compares convolutional neural networks and Alex Net for the diagnosis and Detection of potato and mango disease. The researcher uses 4004 images. The potato image was collected from the plant village online repository while the mango image was collected from the local dataset. The researcher experimented using CNN and Alex Net architecture to detect and classify the disease of mango and potato disease and compares the performance and efficiency of those architectures. Finally, the researcher concluded that the accuracy of Alex Net is better than CNN with an accuracy of 99% for detecting mango and potato disease.
(Wongsila et al., 2021) suggests a deep-learning approach to identify mangoes that have anthracnose. A convolutional neural network (CNN) was utilized by the researcher to train a classification model using a dataset of 1000 images of healthy and sick mangoes. A huge advance over earlier techniques, the CNN's accuracy on the test set was 97.62% using deep learning to identify mangoes that have anthracnose. A convolutional neural network (CNN) was utilized by the author to train a classification model using a dataset of 1000 photos of healthy and sick mangoes. A huge advance over earlier techniques, CNN's accuracy on the test set was 97.62%. on the other hand, the researcher(Singh et al., 2019) propose a deep learning method for identifying mango leaves that are anthracnose-infected. The author utilized a multilayer convolutional neural network (MCNN) to train a model for classification using a dataset of 1070 images of healthy and anthracnose-infected mango leaves. On the test set, the MCNN's accuracy of 96.89% was significantly higher than that of earlier techniques.
(Admass, 2022) researched developing KBS for the diagnosis and treatment of mango pests using data mining techniques. In this study, a knowledge-based system (KBS) for mango pest diagnosis and management is presented. The KBS was created utilizing data mining techniques, such as association rule mining, decision tree induction, and rule induction. A dataset of 100 mango trees was used to test the KBS, and 90% of the trees had accurate diagnoses and treatment recommendations.
(Arivazhagan & Ligi, 2018) Propose a deep learning model for detecting mango leaf disease. The researcher uses 500 images of healthy mango leaves and 700 images of leaves with five different diseases—anthracnose, alternaria leaf spot, leaf gall, leaf webber, and leaf burn were included in the authors' dataset of 1200 images of mango leaves. They trained a model to classify the images using a convolutional neural network (CNN). On the test set, the CNN had an accuracy of 96.67%.
(Prabu & Chelliah, 2022) proposed a novel technique for recognizing and categorizing mango leaf diseases. The technique makes use of a crossover-based Lévy flight distribution algorithm to optimize the convolutional neural network (CNN) architecture. The crossover-based Lévy flight distribution method can enhance the efficiency of the CNN architecture by preventing overfitting, and the CNN architecture is capable of learning the characteristics of both healthy and damaged mango leaves. A collection of 4000 images of mango leaves, containing 1800 unique leaves representing seven diseases, was used to assess the approach and achieved an accuracy result of 96.8% for identifying and classifying mango leaf diseases.
The researcher (Ashok & Vinod, 2021) A unique approach for detecting mango fruit diseases utilizing a deep learning model and an Android application. A convolutional neural network (CNN) model is utilized in the procedure, and it was trained using a dataset of images of mango fruits with and without disease. The Android application then uses the CNN model to identify illnesses in photos of mango fruit. A dataset of 1000 images of mango fruits, including 500 images with diseases and 500 images without diseases, was used to assess the approach. The method's accuracy, which was 95%, was achieved for mango fruit disease identification.

On the other hand, the researcher (Ashok & Vinod, 2016) for the classification of mango defects using a neural network. The researcher compares feature extraction methods to develop a mango disease classification model. The author compares four feature extraction methods (local binary path, speeded robust feature, histogram of oriented gradient, and deep convolutional neural network) with 1000 images of which 250 are labeled as defective. According to the study's findings, CNN had the greatest accuracy rate of 98.67%. The accuracy of the LBP approach was 97.33%, that of the SURF method was 96.67%, and that of the HOG method was 95.33%. Finally, the researcher concluded that CNN is the best effective feature extraction method for the classification of mango defects. The researcher (Trang et al., 2019) researched mango disease classification Using a deep residual network (ResNet) with contrast enhancement and transfer learning, the research describes a method for locating mango disease. Anthracnose, Cercospora leaf spot, and Powdery mildew were the three illnesses that the authors utilized to identify 300 out of a dataset of 1000 mango photos. 224x224 pixel scaling and contrast enhancement were applied to the photos as part of the pre-processing stage.

3 Methodology

3.1. Data collection

The data was collected from the Ethiopian Agricultural research institute Assosa Brach in Ethiopia. The researcher collects 400 image data and 1500 images collected from an online repository used by the author(Arivazhagan & Ligi, 2018). Image augmentation technique has been applied to the images to increase the dataset which was not enough for feature extraction stages. Image augmentation is applied to a dataset to increase the size of the training dataset by creating a modified version of images in the dataset. The original images were transformed by shifts, flips, zooms, cropping the images, and rotating the images. For this experiment, we have used a total of 2500 augmented images (500 images of Anthracnose disease,400 images of Bacterial Canker mango disease, 200 images of Powdery Mildew disease, 200 images of Algae spot disease infected Mango, and 100 healthy mango dataset). The dataset was divided into training, validation, and test set.

3.2. Data Pre-processing

Data processing involves cleaning the data and removing any images that are blurry or that are not of good quality. Data processing is used to enhance the quality of the images/data and includes the elimination of noise or unnecessary information from the images without obliterating the essential information (Balde et al., 2022). In the data processing phase, we resized the images of the dataset into 220 x 220 pixels using Open CV to reduce the processing time and computational cost. And also, the images are converted into a NumPy array which Karas can work with easily.

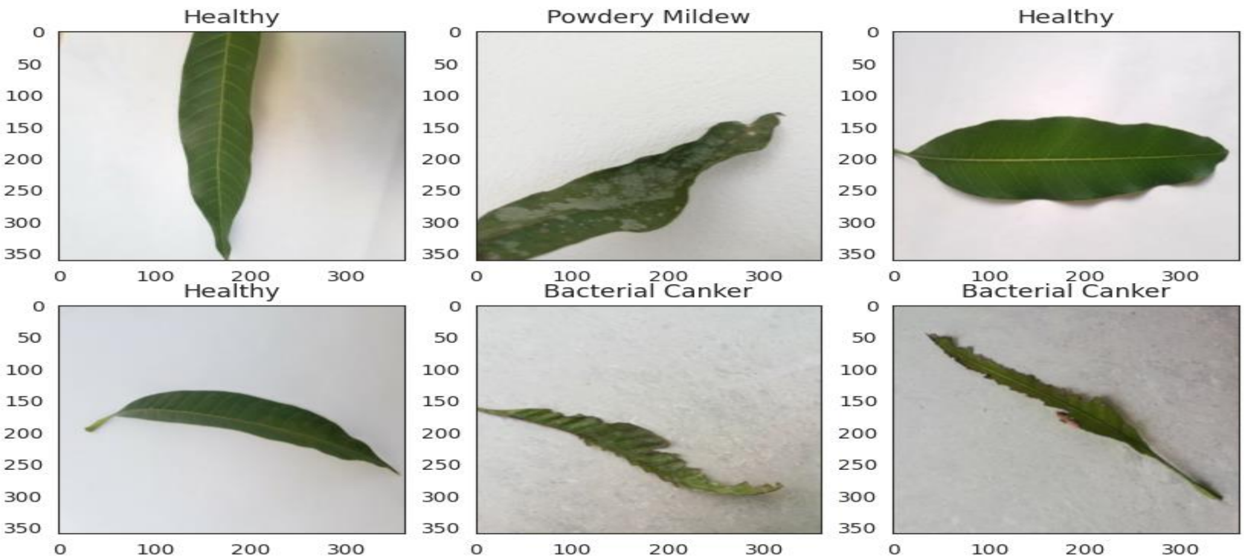


Fig. 1.labeling and processing datasets

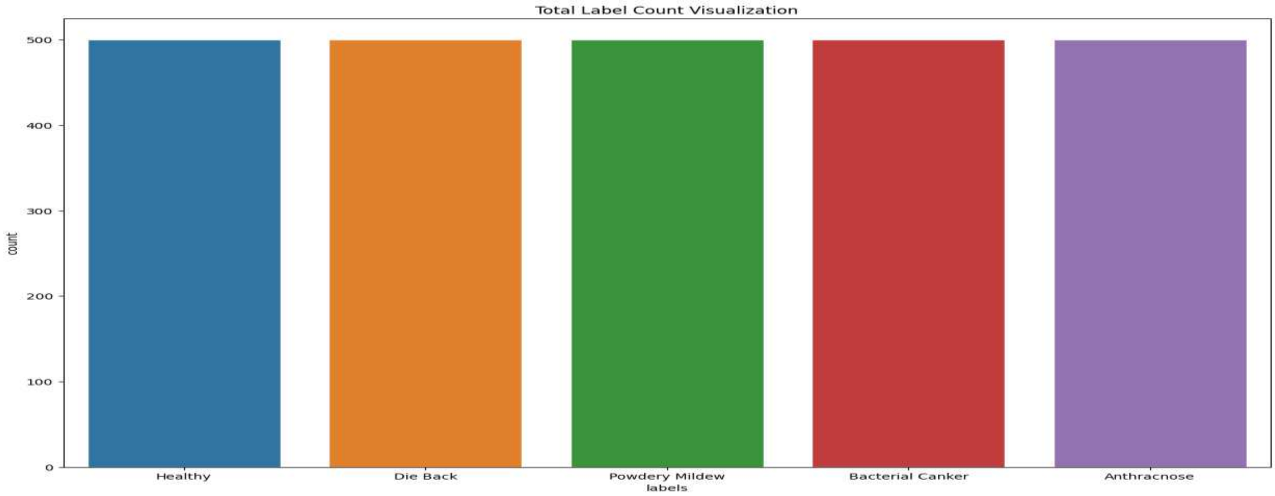


Fig. 2. Shows the Total label count of the data set with their class

3.2.1. Histogram equalization

The histogram image equalization technique is applied to the image data set to improve the contrast of an image by creating a histogram of the image's pixel intensities. This method is one the most usable image processing techniques which is used to transform pixel brightness by spreading out the most frequent intensity values, stretching out the intensity range of the image.

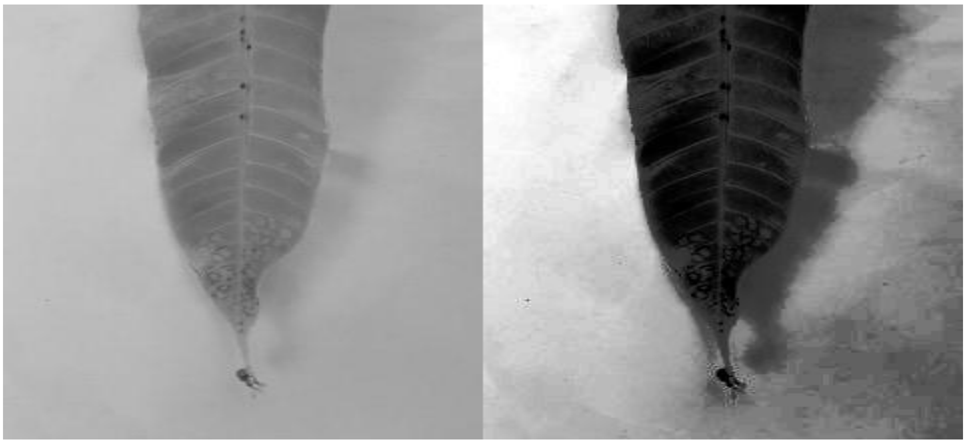


Fig.3. Histogram equalization Techniques in data processing

3.2.2. Anisotropic diffusion filter

Anisotropic diffusion is a nonlinear diffusion technique that preserves edges while eliminating noise. It works by incrementally reducing-edge sharpness while maintaining the overall smoothness of the image. The diffusion coefficient, a quantity that is larger in smooth regions and smaller in edge regions, controls the amount of smoothing that takes place. Purposefully, an isotropic diffusion filter is used to remove the noise from the image without deleting essential (edges, lines, and key components) portions of the image contents. Using this technique, it was possible to reduce diffusivity while minimizing the blurring impact in the areas close to the margins. To eliminate the noise, we compare two image noise removal techniques, i.e., the anisotropic diffusion filter and the Gaussian blur noise removal techniques.

3.3. Data Segmentation

Segmentation is a means of dividing the image into small pieces of segments and each segment contains similar features such as intensity, color, and textures. Image segmentation can be performed using different techniques, some of these are region-based segmentation, edge detection segmentation, clustering-based image segmentation, and threshold-based segmentation. In this paper, we use threshold-based segmentation which is the most basic image segmentation approach which divides pixels depending on their intensity relative to a predetermined value or threshold. It is appropriate for segmenting objects that are more intense than other objects or backgrounds. Threshold-based segmentation is easy to implement and computationally fast. However, because the mango images are grayscale when converted to binary images, portions of the image were matched with the background. In contrast, good segmentation results in complete image separation (background and foreground) with no information loss. In this paper, we apply Binary inverse thresholding techniques. In binary inverse threshold techniques if the pixel value is greater than the assigned threshold, then the value is set to zero otherwise the value is set to a maximum value

$$\begin{gathered} \mathrm{DST}(x,y) =, \text{if threshold} > \mathrm{src}(x,y) \\ \mathrm{DST}(x,y) = \text{max value}, \text{if threshold} < \mathrm{src}(x,y) \end{gathered} \quad (1)$$

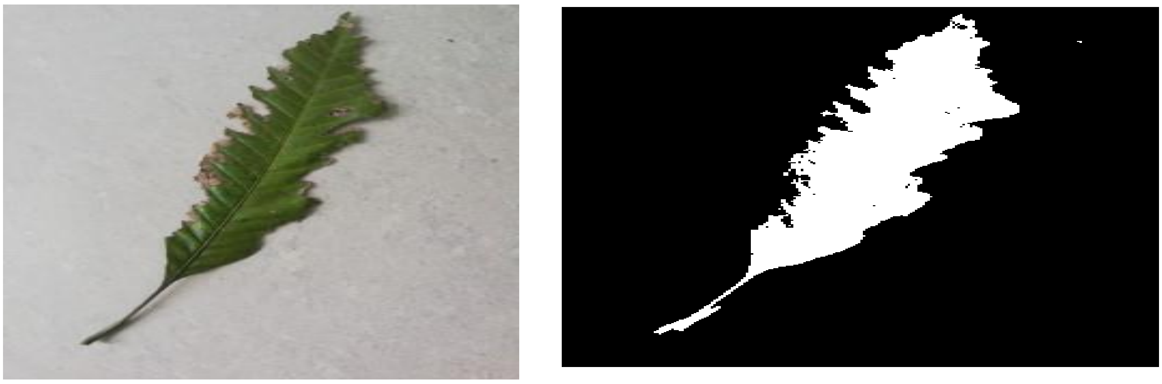


Fig.4. Data segmentation techniques

3.4. Data Augmentation

Since almost all deep learning models need large datasets during training, we use the online freely available dataset and train the proposed model. Then taking the trained model as a per-trained model, we again retrain the model with the collected dataset. In addition to this, we use data augmentation to increase the size of the collected dataset and train the proposed model. For this purpose, we implement filliping and rotation at 45, 90, 135, 180, 270, and 360 degrees in each collected dataset. The augmentation technique has been used in this stage. This technique of training may be called transfer learning in deep learning models. For the online dataset, we will use the mango leaf image released by the Kaggle data science bowl. But for the proposed model, the size of the dataset may not be sufficient. Hence, we will apply the data augmentation method mentioned. This is a common method whenever we encountered a shortage of datasets. Accordingly, through filliping, and rotation at 45, 90, 135, 180, 270, and 360 degrees, we will increase the size of the normal dataset and finally the size of the mango disease dataset from 6000. Then, we divide the dataset into training, validation, and test dataset and transfer the learned parameters with the locally collected dataset. There are different data augmentation techniques such as cropping, adding noise, translation, rotation, and filliping. But to increase the size of the data set, filliping, and rotations are commonly used. Other introduces extra or reduced information from the original raw data, and hence, rotation and clipping are selected.

3.5. Feature extraction

3.5.1. Feature Extraction with Convolutional Neural Networks (CNNs)

A convolutional neural network (CNN) is a neural network that was created to process multi-dimensional data such as image and time series data. During the training phase, it includes feature extraction and weight computation (Gill et al., 2022). CNN is used to extract features, and train and validate models. CNN used three layers to extract features from the mango disease image: a convolutional layer, a pooling layer, and fully connected layers (Brahimi et al., 2017). The convolutional and max pooling layers are flattened and 256 neurons are fed into the dense layer. After being fed into the dense layer, the sequential model was implemented using the Convolutional network layers given by the Keras API of the tensor flow library in Python. For the CNN model, the following layers were considered.

- **Pooling Layer**: - Following the convolution layer, the images from the pooling layer are sent into the max pooling layer, which defines the size of the window, the kind of pooling operation, and the kernel size and stride length (Dhruv & Naskar, 2020). As filters, the maximum pooling layer has a 2X2 window size. The pooling layer also aids in down-sampling the input image. In other words, it aids in reducing the size of the image being used as input, hence reducing the total number of image parameters and thus lowering the computational complexity of the CNN model. The model employs the max-pooling and average-pooling sub-sampling techniques. The dimension 2x2 layer for pooling operates for each feature map and scales its dimensionality using the 'MAX' function. The pooling layer requires two hyper-parameter parameters such as filter (F) and stride (S). The pooling layer generates a result of size W2xH2xD2 if the size of the input image is W1xH1xD1.

$$W2 = ((W1\ F)/S) + 1 \tag{2}$$
$$H2 = ((H1\ F)/S) + 1 \tag{3}$$
$$D2 = K \tag{4}$$

Where F indicates the filter size, S is the stride size, and K is the total amount of filters used. It's worth noting that we just utilized one Max pool 2D layer for each of the Conv2D layers.

- Activation: - Convolutional neural network uses different activation functions such as ReLu, SoftMax, Sigmond, and tanh. In this paper, we use the ReLU activation function to constitutionally classify images. The reason we use ReLU is it avoids and corrects the decreasing gradient problem; a function called ReLU was utilized. ReLU-based neural network models are simpler to train and perform better than models that use other activation functions such as sigmoid or hyperbolic tangent activation functions.
- Pool size selection: - for the feature extraction we use a 3x3 filter size based on the characteristic features of the mango disease image recognized.
- Flatten Layer: - After the max pooling layer we use Flatten layer to adjust the input in to fully connected layer for classification. This allows the fully connected layer to process the generated feature map within a short time. Following the convolutional, pooling, and flattening layers, the input image is sent into the fully connected layer. The flattened layer transforms two-dimensional data into one-dimensional data. The fully connected layer classifies the flattened image dataset.
- Optimizer and reduced Overfitting: - for the CNN model we use Adam optimizer which is easy to implement, efficient, and requires less memory and also it is more effective for large datasets and parameters. In addition to this, dropout is used to reduce overfitting of the training data sets with dropout probability of 0.2, 0.25, and 0.3 before fully connected layers.

3.5.2. Feature extraction using Histogram of Oriented gradients

The histogram-oriented gradient is the most common feature extraction technique in computer vision and image processing and is effective in extracting and capturing shape and edge information from images. We use HOG feature extraction in addition to CNN. HOG is more energy efficient than CNN features in hardware implementations and neural networks produce more redundancy of images than standard techniques because the neural network is more computationally expensive. Current deep learning algorithms can take an extended period to train from the start before they can successfully train CNNs. HOG (Histogram of Oriented Gradients) is a widely recognized feature extractor that delivers excellent performance while maintaining relatively simple computation. HOG-based algorithms remain popular in numerous applications due to their ability to strike a balance between accuracy and complexity. In this paper, HOG features have been extracted for each pre-processed image of size (64 × 128). HOG descriptors are extensively employed in computer vision and image processing for object detection tasks. By analyzing the distribution of local gradients, HOG extracts essential characteristics related to an object's appearance, shape, texture, and structure.

3.5.3. Hybrid Feature Extraction (CNN and HOG)

The model produces a feature vector output of 18,824 from the CNN model and a feature vector output of 5,780 from the HOG feature extractors after completing CNN and HOG feature extraction. A combined feature vector of 24,604 features is created by combining the features extracted with CNN and HOG. To capture a more complete representation of the images, CNN and HOG's features are combined. CNN concentrates on learning hierarchical characteristics from the image pixels, while HOG captures shape and texture information. The model can use both local and global information to better describe the intricate internal aspects of the images by integrating these two different types of features. The 24,604-feature fused feature vector offers a more potent representation for subsequent classification or analysis tasks, allowing the model to more accurately distinguish between and categorize the mango disease categories.

The feature vectors acquired from each approach are concatenated using the hstack function to merge the features extracted from HOG and CNN. The result is saved in CSV format for later processing when the features have been combined. After then, the dataset was split into training, validation, and testing sets. To classify, we employ the SVM (Support Vector Machine) and random forest classifiers, which are well-known techniques for pattern recognition applications. The performance of mango disease recognition will be enhanced by the use of these classifiers. For the classifiers to produce more precise predictions, the combined integrated features provide a more thorough representation of the photos of the mango disease.
The improved performance attained by combining HOG and CNN features shows how useful it is to use both shape and texture data from the images. This method enables a more accurate and discriminative depiction of mango disease symptoms, improving capacities for identification and classification.

3.6. Classification

Support vector machine, or SVM, is a well-known supervised machine learning technique that may be used for both classification and regression applications. Although it can be modified to accommodate multi-class classification, it is notably useful for tackling binary classification problems. To distinguish between several classes, SVM creates a hyperplane in a multidimensional space. To reduce classification errors, SVM iteratively generates the optimum hyperplane. Binary classification is used to train the Linear SVM, Sigmoid kernel function, polynomial kernel function, RBF, and random forest classifiers utilizing the features acquired after the features were concatenated. We classified each dataset. Using the understanding of the learning model, we assigned each image in the test dataset to a predetermined class (Anthracnose, Bacterial Canker, Die Back, Healthy, and Powdery Mildew). Thereafter, comparing RBF, linear SVM, sigmoid kernel function, polynomial kernel function, and random forest.

4.7. Model Evaluation Techniques

In this study, the holdout validation technique was employed instead of cross-validation. The dataset contained an ample number of samples for both training and testing, making it suitable for holdout validation. The performance evaluation of the CNN, HOG, and hybrid models was conducted on the testing dataset once the model training was completed(Balde et al., 2022). To assess the performance, various widely-used metrics such as accuracy, precision, sensitivity (recall), and F1 score were employed. Accuracy measures the overall correctness of the model's predictions or the classification accuracy of the validation (training) data. A confusion matrix was utilized to calculate the number of true positives, true negatives, false positives, and false negatives, which aided in evaluating the effectiveness of the proposed model(Liu & An, 2020).

Accuracy: - When evaluating a model's performance on a collection of data, accuracy is used as a metric. To determine it, divide the number of accurate forecasts by the total number of predictions.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN}) \quad (5)$$

Precision: - A model's positive predictions' precision is a measure of their accuracy. Its definition states that it is the proportion of real positive results to all of the positive expectations.

$$\text{precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (6)$$

Recall: - The completeness of a model's accurate predictions is gauged by a recall. It is determined by dividing the total number of actual positives by the proportion of true positives.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (7)$$

F-1 Score: - The F1 score is a performance metric for models that combines recall and precision. It is described as the harmonic mean of recall and precision, where the best F1 score is 1 and the worst is 0. Precision and recall both contribute equally to the F1 score.

$$\text{F1} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall}) \quad (8)$$

4 Model Evaluation and Discussion

In this section, we discuss the different tests that were run to evaluate the model. Here, we conducted different experiments and compare the result with different evaluation metrics such as accuracy, precision, recall, and F-score.

4.1. Evaluation of Convolutional Neural Network (CNN) Models

In a study, we experimented, by combining CNN by applying image augmentation features to enhance the classification of mango disease using the SVM classifier. We obtained results with an accuracy of 85%. To develop a model by CNN techniques, we apply image processing, image segmentation, and augmentation techniques to enhance the quality of data, remove noise and increase the size of datasets. After we perform data processing using the CNN technique, we develop the CNN model batch_size=64, ReLU activation, and Adam optimizer. After the model is developed using CNN feature extraction techniques, the model will be evaluated with performance evaluation metrics. The performance of the model will be presented as follows.

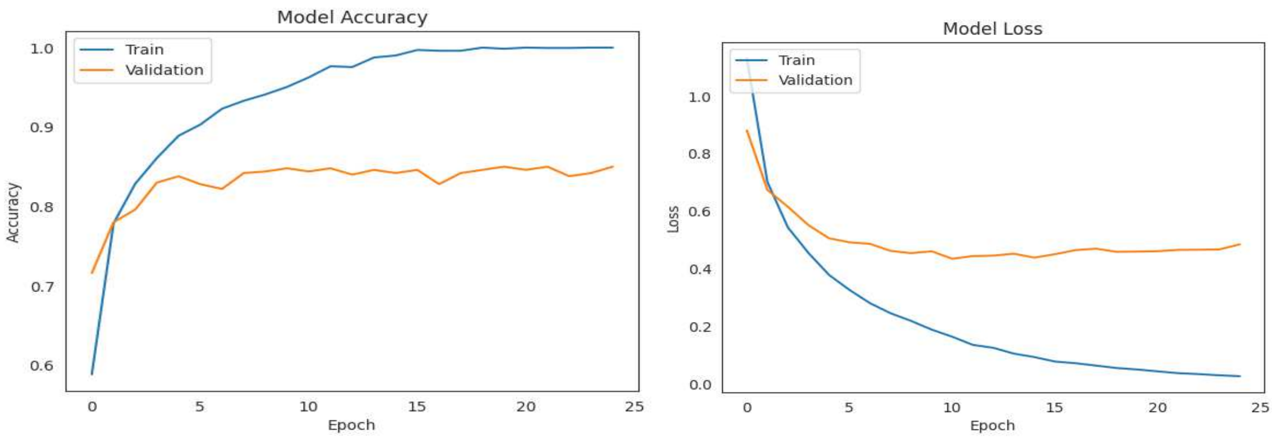
```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       100
           1       0.92      0.91      0.91        88
           2       0.88      0.77      0.82       108
           3       0.79      0.82      0.81       111
           4       0.73      0.80      0.76        93

    accuracy                           0.85       500
   macro avg       0.85      0.85      0.85       500
weighted avg       0.85      0.85      0.85       500

Recall: [0.97       0.90909091 0.76851852 0.81981982 0.79569892]
Precision: [0.95098039 0.91954023 0.88297872 0.79130435 0.7254902 ]
F1-score: [0.96039604 0.91428571 0.82178218 0.80530973 0.75897436]
```

As shown in the above figure, the developed model produces an overall accuracy of 85%, the model developed by combining attained less accuracy result than the models developed by using CNN and HOG techniques. Based on the graph below the training accuracy of the hybrid model is 0.8500 and the training loss accuracy is 0.4848. The figure below shows the model Accuracy and model loss of models developed by combining the convolutional neural network and histogram-oriented gradient techniques.



(a) **(b)**

Fig.5.(a) Represents the model Accuracy attained by the CNN model (b) Represent the model loss attained by the CNN model

4.2. Evaluation of Models Developed by Histogram-oriented Gradient (HOG)

This study focuses on comparing a model developed using CNN, HOG, and a combination of CNN and HOG techniques. In this experiment, we develop a model using histogram-oriented gradient feature descriptors using SVM classifiers. In this, experiment we extract features using HOG. We use an 8x8 cell size with 2X2 cells per block, HOG features were extracted from mango disease images. The features were fed into an SVM classifier after image augmentation. It was found that the resulting testing accuracy was observed as follows.

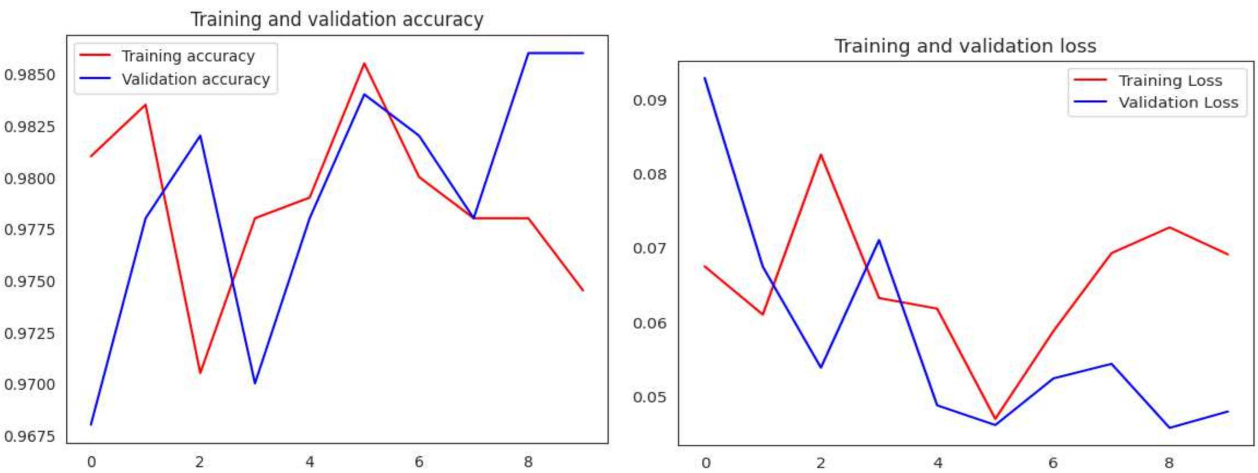
```
Accuracy: 0.862
Training Accuracy: 0.9905
Validation Accuracy: 0.862
```

Anthracnose	0.70	0.78	0.74	93
acterial Canker	0.98	1.00	0.99	100
Die Back	0.94	0.88	0.91	88
Healthy	0.83	0.79	0.81	108
Powdery Mildew	0.87	0.86	0.87	111
accuracy			0.86	500
macro avg	0.87	0.86	0.86	500
weighted avg	0.87	0.86	0.86	500

The model developed by HOG produces a training accuracy of 0.9905 and a validation(testing) accuracy of 0.862. the overall accuracy of the model developed by the histogram-oriented gradient feature extractor is 86.2%. Based on the evaluation metrics such as precision, recall, and F1-score, the model has a precision of 70% as anthracnose,98% as bacterial canker, 80% healthy, and 87% as powdery mildew, in addition to this, the model a recall rate of each disease 78% as anthracnose, the bacterial canker has 100% recall rate, Die back has 88% recall rate, health has 79% recall rate, and powdery mildew has 87% recall rate. in terms of F1-score the proposed model attained 74%,99%,91,81%, and 87% for Anthracnose Bacterial canker, die-back, Healthy, and powdery mildew respectively. The above result has been represented by using the confusion matrix in the figure bellow

4.3. Evaluation models Developed by Combining CNN and HOG (hybrid approach)

In the proposed study, a dataset of 2500 data sets was collected from the Ethiopian agricultural research institute, the Assosa branch, and an online repository (Kaggle). The dataset has five (5) classes i.e., Healthy, Powdery mildew, Anthracnose, Bacterial canker, and die back. Augmentation is performed on images to increase the size of datasets which is used for training and testing. Then the dataset is split into test and training sets. 80% of the data has been used for the training set and the rest of 20% of the data has been used to test the developed model. The model is developed by combining CNN and HOG (hybrid) by applying image augmentation features to enhance the classification of mango disease using the SVM classifier. We obtained results with an accuracy of 98.80%. To develop a model by combining the CNN and histogram-oriented gradient techniques we use HOG feature extraction with a cell size of 8X8, orientation =9, and 2X2 cells per block. After we perform data processing using the HOG technique, we develop CNN model batch_size=64, ReLU activation, and Adam optimizer. After the model is developed by combining the CNN and HOG feature extraction techniques, the model will be evaluated with performance evaluation metrics. The developed model produces 98.80% accuracy. The training and validation accuracy graph attained by the developed CNN model is presented in Figure 6(a) below and the training and validation loss of the combined CNN and HOG model is also presented in Figure 6(b) below.



(a) (b)

Fig.6. (a) Training and validation accuracy of hybrid (CNN &HOG) model (b) Training and validation loss of the (CNN &HOG) model

The proposed hybrid (CNN and HOG) model proposes an extended model that has high validation accuracy and minimal validation loss, outperforming training accuracy (Fig. 4(a)). Utilizing metrics like precision, recall, and F1 score, the model builds a confusion matrix to evaluate its performance. The suggested model performs well in classification tasks, as evidenced by its 0.9880, 0.978, and 0.972 accuracy, recall, and F1 score values. The precision, recall, F-Score, and accuracy of the hybrid Model are presented in the figure below

	precision	recall	f1-score	s
Anthracnose	1.00	0.91	0.95	
Bacterial Canker	0.98	1.00	0.99	
Die Back	0.96	0.99	0.98	
Healthy	1.00	1.00	1.00	
Powdery Mildew	0.96	0.99	0.98	
accuracy			0.98	
macro avg	0.98	0.98	0.98	
weighted avg	0.98	0.98	0.98	

Fig.7. Precision, Recall, F1-score and accuracy of the proposed hybrid approach(CNN & HOG) model

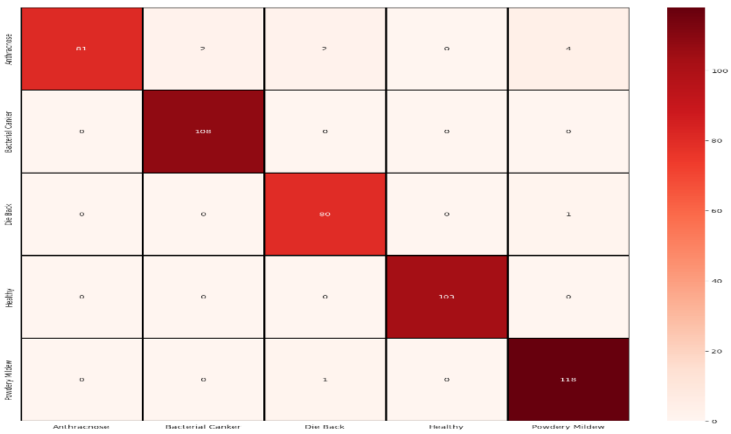


Fig.7. Confusion matrix of the Proposed hybrid Approach (CNN & HOG) model

4.4. Result Discussion

In this paper, a total of 2500 mango leaf disease image is used to train and develop the model, out of 2500 image 400 images are collected from the locally Ethiopian agricultural institute, Assosa branch, and the rest of the image dataset was collected from an online dataset repository (Kaggle dataset). After we collect the data, data preprocessing, data segmentation, data augmentation, and feature extraction techniques are applied to the collected data to increase the quality of images by removing noise, and increasing the size of datasets. After applying these techniques, we compare the conducted three experiments to compare the developed modes by using CNN, HOG, and hybrid (combining CNN and HOG) techniques. 1st we developed a model by using CNN techniques, 2nd we developed a model by using the HOG feature extractor, 3rd we developed a model by combining the CNN and HOG techniques. All those experiments and models are developed by the segmented and augmented datasets and select one model to develop an automatic mango disease detection system. To select the best-performed model, we use performance evaluation metrics such as accuracy, precision, recall, and F1-score measurements. The table below shows the comparison of developed models using their training accuracy and test accuracy.

Table 1 Training and validation performance of the models

No	Model	Training Accuracy (%)	Validation accuracy (%)
1	Combined (CNN & HOG)	98.60%	97.45%
2	HOG	99.05%	86.2%
3	CNN	85.00%	84.00 %

As shown in the above table the hybrid (CNN &HOD) model performs better with a training accuracy of 98.80% and validation accuracy of 97.45%. Therefore, the model developed by combined (CNN &HOG) has performed better than models developed by histogram-oriented gradient and models developed by CNN. The detailed comparison of the model performance in terms of Accuracy, recall, precision, and F1-Score is presented as follows

Table 2 Performance Evaluation of CNN, HOG,, and Hybrid Model

No	Model	Class (Disease)	Precision	Recall	F1-Measure
1	Hybrid (Combined CNN & HOG)	Anthracnose	1.00	0.91	0.95
		Bacterial Canker	0.98	1.00	0.99
		Die Back	0.96	0.99	0.98
		Healthy	1.00	1.00	1.00
		Powdery Mildew	0.96	0.99	0.98
		Average	0.98	0.98	0.98
2	HOG	Anthracnose	0.70	0.78	0.74
		Bacterial Canker	0.98	1.00	0.99
		Die Back	0.94	0.88	0.91
		Healthy	0.83	0.79	0.8
		Powdery Mildew	0.87	0.86	0.87
		Average	0.87	0.86	0.86
3	CNN	Anthracnose	0.95	0.97	0.96
		Bacterial Canker	0.92	0.91	0.91
		Die Back	0.88	0.77	0.82
		Healthy	0.79	0.82	0.81
		Powdery Mildew	0.73	0.80	0.76
		Average	0.85	0.85	0.85

5. Conclusion and Future work

Many researchers have researched the detection of mango disease using machine learning and deep learning techniques. In this paper, we presented a deep learning approach for the automatic detection and classification of mango disease to early detect and prevent the disease. Convolutional neural network and histogram-oriented gradient techniques are utilized as feature extraction mechanisms and the Support vector machine (SVM) classifier is employed for the classification of mango disease. This study aims to enhance the efficiency of diagnosing and detecting mango disease to prevent the disease and facilitate the early detection of mango disease. In this paper, we conducted three experiments with CNN, HOG, and a combination of CNN and HOG (hybrid), and High training accuracies were achieved (98.60%), Sigmoid CNN (98.3%), Random Forest (98.3%), and Linear SVM (98.1%) testing accuracy. The best results came from CNN, which outperformed other techniques with accuracy rates of 98.60% during training and 97.45% during testing. In terms of training accuracy, CNN (AlexNet) achieved 98.60%, linear SVM 92.9%, sigmoid CNN classifier 92.5%, and random forest 92%. To categorize and detect mango diseases in the future, researchers should investigate several deep learning approaches such as RNN, BILSTM, GAN, and LSTM algorithms. Using these strategies can improve accuracy and efficiency, resulting in improved disease management and healthier mango crops.

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