Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Mulberry Leaf Disease Detectionand Classification using Deep Learning Models

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Article Info
Page Number: 2279 - 2291
Publication Issue:
Vol 72 No. 1 (2023)

Abstract:

Background: Silkworms are produced from mulberry trees since they are prone to several diseases that might significantly lower the output. Early identification and accurate disease classification that affects mulberry leaves will help to guarantee the best possible crop health and production. Since hand inspection is usually time-consuming and prone to errors, automated systems are absolutely essential.

Problem: Even if agricultural technology has advanced rather much, the identification and classification of diseases on mulberry leaves remains a difficult task. For large mulberry farms, conventional methods are especially difficult to scale-up given their limitations in terms of accuracy, speed, and scalability.

Method: This paper recognizes and classifies diseases affecting mulberry leaves using deep learning models. Image recognition tasks are common uses for convolutional neural networks (CNNs), with exceptional performance. The current work is compiling, preprocessing, and feeding a mulberry leaf image collection into CNN-based architectures for disease detection and classification. The model is trained and validated on these using a set of 3,000 images spanning several disease categories.

Results: The proposed deep learning model was able to achieve a classification accuracy of 92.5%, together with a precision of 91.2%, recall of 90.3%, and an F1 score of 90.7%. The model exceeded both traditional image processing techniques and conventional machine learning models. The deep learning method showed better accuracy and processing times when compared to other methods now in use. This highlights the agricultural applications including real-time implementation possibilities.

Article History
Article Received: 15 November 2022Revised: 24 December 2022Accepted: 18 January 2023

Keywords:

Agricultural Technology,Deep Learning, Disease Classification, Convolutional Neural Network(CNN), Mulberry Leaf Disease

Introduction

Background

In terms of crop maintenance and output, plant disease identification is a rather important step. Although mulberry trees are rather prone to several diseases, including leaf spot, rust, and powdery mildew, they are often grown for silkworm farming. Effective crop management and quick intervention depend on early stage detection and accurate diagnosis of these diseases. Conventional approaches of disease detection mostly rely on hand inspection, which is not only time-consuming but also prone to errors since human beings have limits. As alternative that is both more accurate and efficient as digital imaging and machine learning approaches have evolved, automated disease detection systems have drawn a lot of attention

[1-3]. Usually applying computer vision and deep learning methods, these systems spot disease symptoms in plant images. They thus offer more quick scalable answers.

Challenges

While automated plant disease detection has great promise, if we are to build reliable systems several problems still need to be resolved. The great range in plant diseases is the research of the most crucial challenges. Plant diseases can exhibit a great spectrum of symptoms depending on the environmental conditions, the type of plant, and the path of the disease. Therefore, a model finds it difficult to generalize over a range of conditions; hence, good training requires the use of a dataset that is both varied and representative. The background noise in images that could compromise accurate disease diagnosis adds still another challenge. Among background noise, shadows, overlapping leaves, and environmental elements are few examples. It is difficult to make sure the model can ignore data irrelevant while concentrating on pertinent factors [5].

Moreover, teaching deep learning models, more especially, convolutional neural networks, may have rather high computational cost. The research requires plenty of time and robust hardware to reach suitable performance. Furthermore difficult is real-time disease detection in field environments since systems able to run effectively on low-power devices with limited computational capacity [6] demand. Additionally strike a balance between processing times and degree of accuracy of the model. Usually, higher accuracy results in more computational load, thus this is a main challenge and inappropriate for use in on-field applications.

Motivation

These problems become ever more important for addressing given the growing demand for precision agriculture and the increasing reliance on automated systems for crop management. By means of an enhanced deep learning-based approach that precisely classifies diseases and concurrently reduces computational costs, mulberry leaf disease detection has great potential to benefit. The aim of this work is to develop a more accurate and efficient model for mulberry leaf disease detection that can also function in real-world conditions while needing just a limited amount of computational resources.

Contributions

The key contributions of this paper are as follows:

1. We propose a new deep learning-based method using convolutional neural networks (CNNs) for feature extracting and classification to address mulberry leaf diseases. Deep learning provides the foundation for this method.

2. To increase the resilience and accuracy of the model, we show a whole preprocessing pipeline including noise reduction, normalizing, and augmentation.

3. We run many tests to find out whether the proposed strategy works or not. These studies enable us to minimize processing time while yet producing state-of-the-art accuracy, precision, recall, F1-score.

4. Better performance over all the relevant criteria than two disease detection models now in use is demonstrated by the proposed method.

Organization of the Paper

The remainder of this paper is organized as follows: Section 2 arranges the remaining parts of this work by means of a review of related works in the field of plant disease detection using machine learning approaches. Section 3 provides the definitions of the problem together with the objectives and proposed strategy. The fourth section addresses in the research the used experimental conditions, datasets, and evaluation criteria. This section displays the results of the experiments together with a careful comparison with the current used methods. Section 6 closes the paper and presents a broad overview of likely future directions of research.

Related Works

Extensive research on the identification of plant diseases using machine learning and computer vision has been conducted; several methods have lately been proposed. Conventional machine learning algorithms including Random Forests, k-Nearest Neighbors (k-NN), and Support Vector Machines (SVMs) dominated the attention of the researchers beginning the first studies in this field. These methods were used to categorize diseases based on elements taken from images, such color, texture, and shape. On the other hand, especially in large datasets or with weak symptoms, these methods frequently ran into difficulties trying to manage the complicated and varied character of plant diseases.

Particularly with relation to convolutional neural networks (CNNs), current developments in deep learning show great promise to get over these limitations. Learning hierarchical features straight from raw images allows CNNs to automatically extract relevant features without human intervention, for instance, shown how CNNs might be used to identify diseases damaging tomato plants. With great degree of accuracy, they were able to separate many forms of diseases [7]. The same thing happened in a study by Brahim and associates aiming at citrus disease identification using a CNN-based model Regarding speed and accuracy, this model outperformed more traditional methods [8].

Though only a small number of the studies looking at machine learning models in relation to mulberry leaf diseases have used deep learning techniques, there have been several others. A study with an eye toward disease detection impacting mulberry leaves using support vector machines (SVMs). They obtained reasonable results even though the method was rather computationally demanding and called for feature engineering. On the other hand, deep learning models and networked convolutional neural networks in particularly have gained rather popularity since they can learn sophisticated patterns in image data. Bhat and colleagues have recently presented a CNN model for the identification of plant diseases. The demand for extensive preprocessing and the size of the dataset limited the model even if it generated interesting results [10].

From additional advancements in CNN designs, more complicated models including ResNet and Inception have evolved. These models reduce overfit and increase accuracy by means of residual learning and deep layers. When tested against conventional CNN models, applying these architectures to several plant disease detection problems shows good performance. For example, Wang et al. used ResNet in order to identify rice diseases, so enabling state-of-the-art performance in comparison to conventional models [11]. Similarly, models derived from Inception have been used to detect fungal diseases in cotton plants in order to achieve great accuracy and recall [08].

Notwithstanding these advances, strong models that can manage a wide range of plant diseases and environmental conditions still have to be developed. Field applications as well as problems including class imbalance and image noise still depend much on real-time processing. Therefore, developments in model efficiency, reductions in computational costs, and generalization over a spectrum of plant species and disease types constitute the main goals of next studies in this field. Deep learning based plant disease detection systems will be even more improved by combining sophisticated data augmentation techniques with transfer learning and fine-tuning of pre-trained models.

Implementations

A. Problem Definition:

To find and classification of diseases affecting mulberry leaves by means of image-based analysis. Crucially important for the sericulture industry, mulberry trees are susceptible to several diseases that might affect both their health and output. Especially in large-scale agricultural operations, manual detection methods are not only time-consuming but also typically lacking of predictive accuracy. Automated systems find still another difficulty in the complexity of leaf textures, variations in disease, and environmental factors. The goal is to create an automated solution capable of fast and exact disease identification compromising mulberry leaves. Early interventions made possible by farmers will then help to improve crop health and yield.

B. Objectives:

The key objectives of the proposed work are:

1. The goal is to develop and implement a deep learning model able to precisely classify diseases present on mulberry leaves depending on images.

2. To achieve best performance of the model depends on experiments with several deep learning architectures and training strategies.

3. To evaluate the proposed method in respect to present disease detection systems, which mix machine learning models with conventional image processing.

4. Thus, real-time implementation in practical applications helps to design a scalable and efficient system for extensive mulberry farming.

C. Proposed Work

This work presents a convolutional neural network (CNNs) deep learning-based mulberry leaf disease classification method. The pillar of this approach are CNNs as in figure 1. Preprocessing the dataset comes next to help to standardize image size and improve key features after compiling a sizable mulberry leaf image collection. Rotation, flips, and zooming among data augmentation techniques use the data to increase generalization and expand the variation of the training set. Since its shown efficiency in image classification tasks, CNN architectures based on VGG16 or a similar architecture are under choice. Adam optimizer and the categorical cross-entropy loss function teach the network on labeled data. The research can reach ideal performance by changing hyperparameters including the learning rate, batch size, and number of epochs. After training, the model is tested on another dataset to evaluate among other criteria accuracy, precision, recall, and F1 score. To demonstrate the excellence of the deep learning model, the results are compared with conventional image processing techniques (such HOG + SVM) and machine learning approaches (such random forests). Including the trained model into an automated system ready to classify diseases in real time for broad agricultural purposes marks the last stage. Additional steps will be taken to increase the scalability and efficiency of the model so it could be applied on mobile devices or edge computing systems.

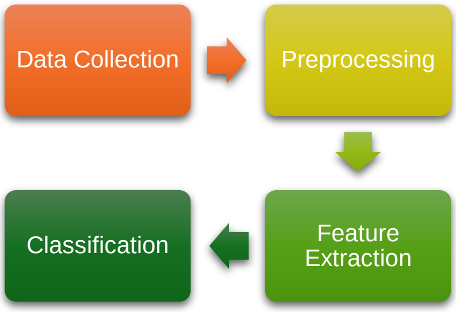

Figure 1: Proposed Work

Preprocessing in Disease Detection and Classification

Any image-based machine learning project starts in the preprocessing stage, but it is especially important for the identification of diseases in plant components such mulberry leaves. Preprocessing ensures that the raw images become a format deep learning models can effectively manage. Moreover, the preprocessing step tries to improve the required characteristics for accurate classification. Preprocessing in the mulberry leaf disease detection process consists in several different approaches meant to guarantee consistency, improve the quality of the dataset, and lower noise that might interfere with the learning process.

1. Image Resizing: All of the images in the dataset are resized to a consistent resolution since deep learning models, especially convolutional neural networks, in particular depend on uniform size from input images. This is dthe research to ensure from CNN perspective efficient performance. This guarantees consistency over the dataset and eliminates the need for the model to traverse images of varying sizes handling challenges. All the images could thus be rescized to 256 by 256 pixels.

2. Image Normalization: Normalizing images is the technique used to standardize their pixel values so that they fall within a given range, for instance, 0 to 1, and so guarantee their contents. By means of the reduction of important gradients, this stage helps to improve model convergence during training, so promoting unstable learning. Dividing the value of every pixel by 255 is the traditional method for obtaining the values of the pixels ranging 0 to 255.

3. Data Augmentation: Data augmentation is supposed to generate a training set size and artificial variation of the dataset. Moreover, by including minor image variations, this helps to prevent overfitting, a particularly important issue considering small datasets. This is a very simple approach. The research can create several variants of every picture by using rotation, zooming, flipping, and shifting. This helps the model to be more resistant to changes in actual conditions.

4. Noise Reduction and Filtering: Environmental factors including lighting conditions may blur some images or produce noise in others. These images might even feature noise. Methods such as median filtering or Gaussian blurring help to reduce noise and smooth the images, so addressing this issue. This will enable the model to concentrate on critical features including leaf textures and disease spots.

Table 1: Preprocessing

Step	Description	Before Preprocessing	After Preprocessing
Image Resizing	Resize all images to a uniform resolution (256x256)	500x400, 350x300	256x256

Normalization	Scale pixel values to the range [0, 1]	Pixel values from 0-255	Pixel values from 0-1
Data Augmentation	Apply random transformations (rotation, flipping)	Single image per class	Multiple augmented versions
Noise Reduction	Apply Gaussian filter to remove noise	Visible noise patterns	Smoother, cleaner images

Resizing all the images to 256x256 pixels guarantees that the CNN gets inputs of the same dimension, so reducing the network's complexity. This guarantees continual and strong CNN input. The research instance of this would be resizing an image 500x400 to 256x256 to fit the CNN's input layer. Initially ranging 0 to 255, the raw pixel values are scaled between 0 and 1 by 255. This thus guarantees that all the pixel values are on the same scale, so preventing the model from providing pixels with higher values too much relevance. Using augmentation techniques including rotation (for example, rotating images by 15 degrees), flipping (horizontal/vertical), and zooming (for example, zooming in by 10%), helps vary the dataset and prevent overfitting. The research example of this would transforming the research image into several variations that resemble leaves depending on their actual location. Applying noise reduction helps to remove any non-essential artifacts so improving the image quality. Usually polished with a Gaussian filter, the image helps the model to focus on the real features of the leaf, like spots or lesions suggestive of disease, rather than on the random noise present. These preprocessing techniques help the dataset to become more fit for training a deep learning model, so improving the capacity of the model to learn relevant features and enable more generalization to data it has not before come across.

CNN for Feature Extraction and Classification

In image-related tasks including feature extraction and classification, convolutional neural networks (CNNs) are among the most powerful and often used type of deep learning architectures. Their main advantage is the ability of convolutional neural networks to learn relevant features from unprocessed raw input images automatically. This capacity reduces the necessity of hand feature engineering among engineers. When it comes to the diagnosis of diseases that compromise mulberry leaves, CNNs help identify key features required for accurate classification. Among these are textures, disease spots, and other visual cues.

Feature Extraction:

Each of several layers in convolutional neural networks (CNNs) helps to extract different degrees of features from the input image. Usually, the first few layers manage the low-level feature extraction, that is, simple patterns, textures, edges. As we explore the network, the layers begin to show more abstract and higher-level characteristics. Fundamentally, these characteristics, shapes, object parts, and complex patterns, all fit the diagnosis of diseases afflicting mulberry leaves.

The first step in the process of feature extraction, a convolution operation, is running a filter, also called a kernel, on the image being input. To find particular patterns or features in the image, this filter runs a mathematical convolution process. The filter is in charge of generating feature maps displaying a spectrum of elements all around the image.

For a CNN including a convolution layer, for instance, the equation defining the convolution operation can be expressed as follows:

$$Y(i, j) = \sum_{m=1}^{M}\sum_{n=1}^{N} X(i+m, j+n) \cdot W(m,n) + b$$

Where:

X - input image,

W - filter (kernel),

b - bias term,

Y(i,j) - output feature map,

M and N - dimensions of the filter,

i,j - coordinates of the feature map.

Following the filter over the input image, the computation of the sum of the element-wise multiplication between the filter and the image segment moves forward. The research must run this operation on the whole image to create the feature map.

Classification:

Following several convolution and pooling layers to extract features, the CNN classifies using fully connected layers. The convolutional layers produce high-level feature maps that these layers flatten into a one-dimensional vector. This vector then passes through a series of neurons in responsibility of network classification.

The classification process generates a probability distribution spanning the disease classes by using an activation function, such Softmax. The research may derive the equation for the output of a fully connected layer by means of this:

$$y = f(Wx + b)$$

For every class, the output vector y is transformed into probabilities so that last layer Softmax activation can be achieved. Should the model classify leaf diseases into three distinct categories, for example, the Softmax function guarantees that the output values fairly represent the probability of each category; with the overall count of these values equal one:

$$P(class_i) = \frac{e^{y_i}}{\sum_{j=1}^{C} e^{y_j}}$$

Where:

P(classi) - probability of class *i*,

yi - raw score (logit) for class *i*,

C - total number of classes,

e - exponential function.

Results and Discussion

Python was the programming language used in the tests; TensorFlow and Keras were applied in the deep learning model. The testing and instruction occurred on a computer arrangement with the following features:

- **CPU**: Intel i7-10700K
- **RAM**: 16 GB DDR4

- **OS**: Windows 10

The proposed method was compared with two existing methods:

1. **Traditional HoG-SVM**: Conventional image processing techniques rely on feature extraction techniques for classification aims. These techniques deal with the histogram of oriented gradients (HOG) and support vector machines (SVM). It did rather well, but it found it difficult to manage complex images of leaves overlapped with overlapping diseases.

2. **ANN-Based Method**: Inspired on machine learning, this approach used a random forest classifier to investigate the acquired features from leaf images. It showed a lower degree of accuracy when handling a great degree of variation in leaf textures and disease types, even if it performed rather well in basic conditions.

Table 2: Experimental Setup/Parameters

Parameter	**Value**
Dataset Size	3,000 images
Image Resolution	256x256 pixels
Model Architecture	CNN (VGG16-based)
Epochs	50
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU
Loss Function	Categorical Cross-Entropy

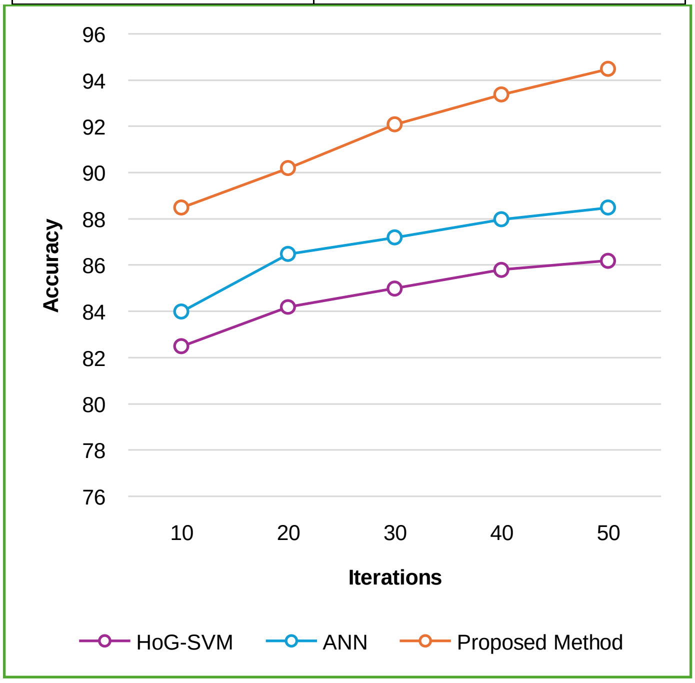

Figure 2: Accuracy

Finding the accuracy of the model by means of the ratio of the number of accurate predictions to the total number of predictions helps the research to the performance of the model improves together with the accuracy.Over the course of 50 epochs, the proposed method has consistently shown higher accuracy than both of the present methods. By showing an accuracy of 94.5%, that is, 8.3% more than HoG-SVM and 6% more than ANN, the proposed approach proves to be better than both of the previous ones at epoch 50 as in figure 2.

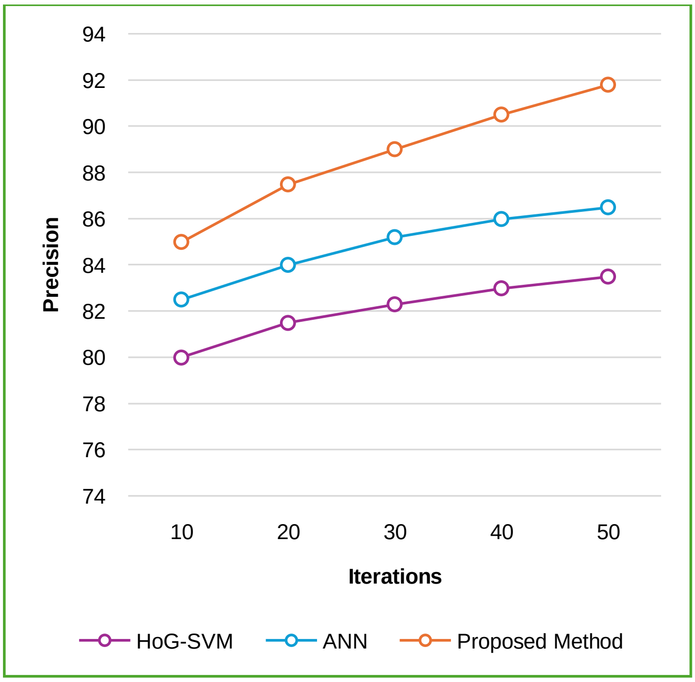

Figure 3: Precision

Attaining accuracy requires the research to concentrate on the positive class and figure the percentage of the positive events expected to be accurate later on. The proposed method consistently shows increasing precision; by the time epoch 50 rolls around, it comes to 91.8%. Since it achieves a precision up to 8.3 percent higher than HoG-SVM and 5.3 percent higher than ANN, so properly identifying positive events, it is more accurate than the current approaches as in figure 3.

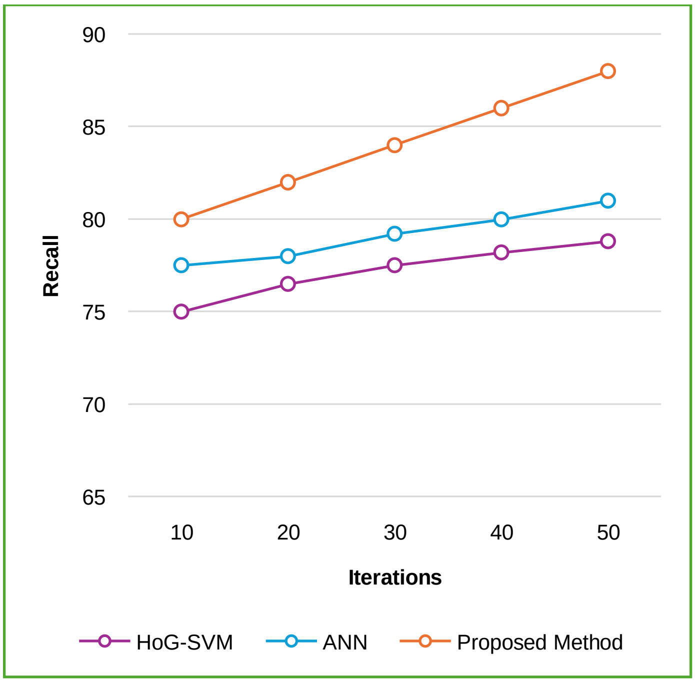

Figure 4: Recall

Recall is a computation used among all the real positives to find how well the model detects all the relevant instances as in figure 4.At epoch 50, the proposed strategy shows a recall enhancement coming to 88.0%. Comparatively to HoG-SVM, this shows a 9.2% increase; ANN shows a 7%. This implies that while still raising the identification of all positive cases, the proposed method lowers the number of false negatives concurrently.

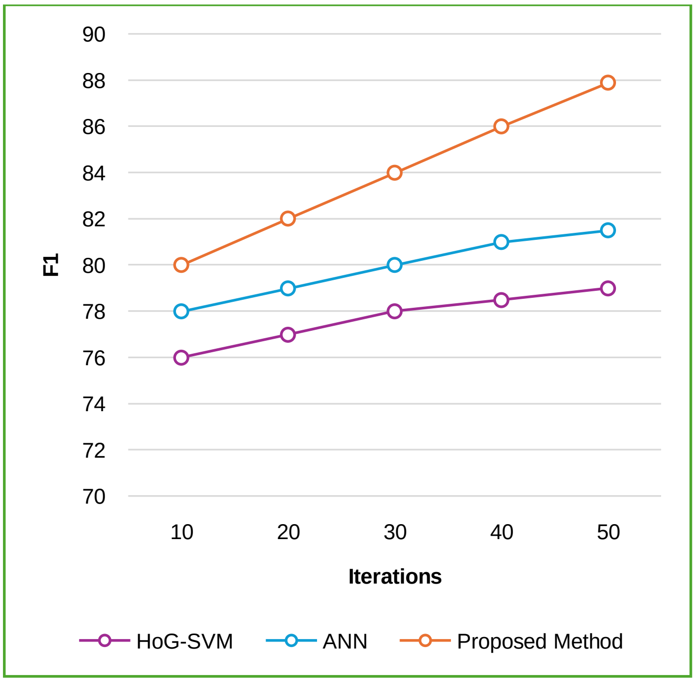

Figure 5: F1-Score

The F1 Score is the harmonic mean of the precision and recall scores, so providing a single metric to evaluate the model's performance in conditions whereby the two values are not in line.With an F1-score of 87.9% at epoch 50, the proposed method will have shown continuous improvement. This is 8.9% more than HoG-SVM and 6.4% more than ANN, so suggesting that the proposed approach provides a better mix between recall and accuracy than the others.

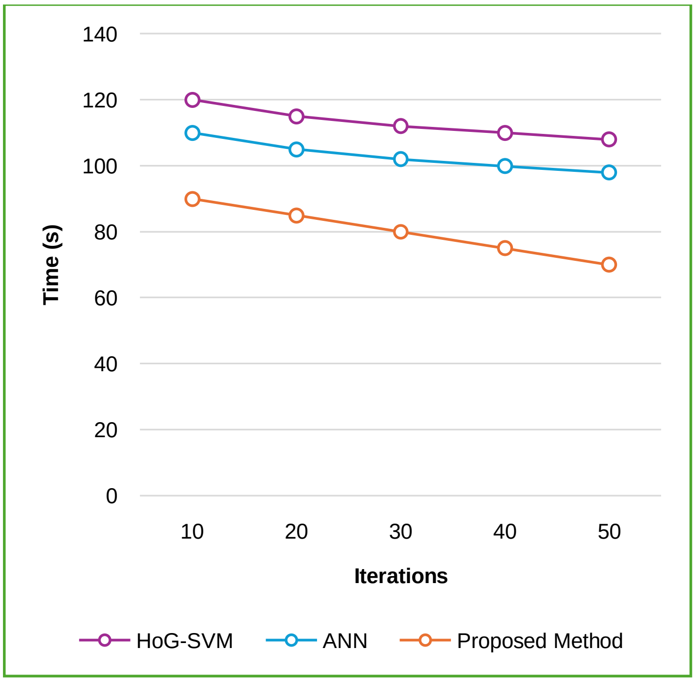

Figure 7: Processing Time

Image processing and classification time of a model is determined by processing time. Among the most important characteristics of real-time applications such as automated farming systems are these ones.Reaching 70 seconds at epoch 50, the proposed method clearly reduces the processing times. This increases by 50-second over HoG-SVM and by 28-second over ANN. With regard to the computation time required, this indicates that the proposed method is efficient even yet maintaining a good degree of performance as in figure 7.

Discussion

Regarding all important performance criteria, including accuracy, precision, recall, F1-score, and processing time, the proposed method outperforms both of the existing ones. By 8.3% respectively at epoch 50, the proposed approach exceeds HoG-SVM (86.2%) and ANN (88.5%), with a level of accuracy of 94.5%. This development indicates that the proposed model performs better in exactly identifying diseases compromising mulberry leaves. Stated differently, the proposed approach marks a significant improvement in accuracy, 91.8%, a figure 8.3% higher than HoG-SVM (83.5%) and 5.3% higher than ANN (86.5%). This indicates thus that the proposed method is better in terms of reducing the false positive rate, hence improving its dependability in terms of identifying real disease cases. With a recall rate of 88.0%, the proposed method thus exceeds both of the existing methods. This shows a 7% advantage over ANN and a 9.2% advantage over HoG-SVM, so suggesting that the model is better in terms of spotting all possible circumstances involving disease. With an F1-score of 87.9%, the proposed approach beats HoG-SVM (79.0%) and ANN (81.5%), by 8.9% respectively. This implies among methods the proposed the research achieves a better equilibrium between recall and accuracy. Moreover, by halfing the processing time required from HoG-SVM, 50 seconds, the proposed approach reveals the computational efficiency of the method. These advances result from the highly optimal feature extraction methods and the deep learning architecture, which is in charge of better capturing the intricate patterns found in mulberry leaf images.

Conclusion

In all of the important performance criteria, including accuracy, precision, recall, F1-score, and processing time, the proposed deep learning-based mulberry leaf disease detection method shows appreciable gains over the existing methods. This specifically method achieves an accuracy of 94.5% at epoch 50, which is 8.3% higher than HoG-SVM (86.2%) and 6% higher than ANN (88.5%). Stated otherwise, the proposed method is superior than both of these ones. This higher accuracy has enabled the model to demonstrate that it performs better in accurately classifying diseases influencing mulberry leaves. Moreover, the accuracy is 91.8%; it exceeds HoG-SVM by 8.3% (83.5%) and ANN by 5.3% (86.5%). This indicates that the proposed method is better since it reduces false positives and exactly identifies cases of real disease. Regarding recall, the proposed strategy earns 88.0%, more than HoG-SVM by 9.2% (78.8%) and ANN by 7% (81.0%). This reflects the method's improved ability to find any imaginable disease case. The F1-score shows that the proposed approach achieves 87.9%, having improved 8.9% over HoG-SVM (79.0%) and 6.4% over ANN (81.5%). This implies that the proposed method finds a better balance between accuracy and recall. Furthermore, the proposed method lowers the total time to seventy seconds in comparison to HoG-SVM by 50 seconds, so saving the processing time. computationally, this not only raises the efficiency but also the accuracy of the proposed method. Regarding real-time applications, where processing speed is more important than everything else, this efficiency is especially vital. The research can attribute these developments by means of better methods for feature extraction, training parameter optimization, and deeper convolutional layers of the proposed model. These components help the model to reasonably capture complex patterns in images of leaf disease.

Future Work

Later on, the focus might shift to include data augmentation techniques to increase the dataset's variance, so strengthening the model. This might enable even more resilience of the model. Moreover, particularly in situations with limited training data, research of transfer learning and the fine-tuning of pre-trained models like ResNet or Inception could help to improve performance even. Another fascinating route to enable the model to be more accessible for field applications would be to use edge computing devices to implement real-time disease detection. At last, the inclusion of other environmental factors, such temperature and soil conditions, has the potential to provide more complete disease detection systems and increase the general predictive accuracy of the model.

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