Simple Neural Network for Identifying Fruit and Leaf Disease in Apple and Mango

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The paper presents a novel approach utilizing machine learning techniques, specifically a Simple Neural Network (SNN) algorithm, for automated detection of apple and mango fruit and leaf diseases. Through extensive data collection, preprocessing, and model development stages, the system achieves a remarkable 95% accuracy in classifying diseased instances within the dataset. Leveraging transfer learning with MobileNetV2 architecture and employing evaluation metrics like accuracy, the model demonstrates robust performance in distinguishing between healthy and diseased samples. Furthermore, the analysis of model performance over time reveals a progression from initial overfitting to eventual convergence, indicating the model's capacity for generalization to unseen data. This research significantly contributes to addressing challenges in agricultural productivity and food security by providing a scalable, efficient, and objective solution for early disease detection, thus empowering growers and experts to implement timely interventions and enhance crop health and yields.

Keywords: Automated detection, Machine learning, Fruit diseases, Identification, Leaf diseases, Smart Agricultural.

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1 Introduction

Fruit and leaf diseases present substantial challenges to agricultural productivity and food security across the globe. Timely detection and accurate diagnosis are pivotal for effective disease management. In recent years, advancements in machine learning (ML) and neural network (NN) technologies have opened up promising avenues for the automated detection of crop diseases. This research paper introduces an innovative approach for the automatic detection of diseases in apple and mango fruits and leaves using a straightforward neural network model.

The cultivation of apples and mangoes holds significant importance for the global economy and the agricultural sectors of many countries. Unfortunately, these crops are highly susceptible to various diseases caused by pathogens such as fungi, bacteria, and viruses, as depicted in Figure 1.1. Traditional disease detection methods rely heavily on expert visual inspection, which is not only time-consuming but also subjective and prone to human error. Consequently, there is a pressing need for automated systems that can accurately identify and classify diseases in fruits and leaves.The proposed approach leverages neural networks to analyze images of both diseased and healthy apple and mango fruits and leaves. The neural network is trained on an extensive dataset of annotated images, enabling the model to distinguish between different disease classes based on visual features extracted from these images. This method obviates the need for manual feature extraction and the use of traditional ML algorithms, thereby streamlining the process and enhancing efficiency.
One of the inherent advantages of this approach is its potential to detect diseases at an early stage, possibly before visible symptoms emerge. Early detection is crucial for the implementation of timely intervention strategies, such as targeted fungicide application or the removal of infected plants, to prevent disease spread and mitigate crop losses. Moreover, the automated nature of the system reduces reliance on human expertise, making disease detection faster, more objective, and cost-effective.

Additionally, the adaptability and scalability of the proposed method make it well-suited for integration into various agricultural systems, ranging from small-scale orchards to large commercial plantations. Its ability to provide real-time insights into disease dynamics and spatial distribution empowers growers and agricultural experts to make data-driven decisions, leading to more effective disease control measures. This not only enhances crop yields and farmer livelihoods but also contributes to the sustainable stewardship of agricultural resources.

Research into the automated detection of apple and mango fruit and leaf diseases aims to address their significant global economic impact by reducing yield losses and promoting food security. Traditional manual inspection methods are laborious and subjective, limiting scalability and efficiency. Machine learning offers a robust solution by enabling early disease detection, facilitating timely interventions, and fostering precision agriculture. Automated systems not only improve crop health but also promote sustainable farming practices by minimizing pesticide use and supporting biodiversity, aligning with broader environmental stewardship goals in agriculture.

Therefore, the primary motivation of this research work is to achieve these objectives. The main goals are to review various research papers on leaf and fruit disease detection, study different datasets related to leaf and fruit diseases, analyze and experiment with the data using various algorithms, and compare the results with existing works.

This paper contains: Section II literature review that describe existing research work; Section II methodology; Section III result and discussion; Section IV conclusion.

2 Literature Review.

In this section, some of the existing research works on Fruits and leaf disease detection with different models and techniques are discussed below.

Thepaper[1] discusses methods such as picture segmentation, feature extraction, and classification that were employed, including the use of K-mean clustering, genetic algorithms, support vector machines, fuzzy curves, fuzzy surfaces, CNN architecture, rule-based models, thresholding approaches, and artificial neural network-based techniques. A genetic algorithm-based system achieved an accuracy of 93%, while an artificial neural network-based technique yielded 89.41% accuracy.

While transfer learning with pre-trained models like DenseNet-121 has shown promise in detecting citrus diseases as evidenced by a 96% accuracy rate in [2], it's not the only approach. Researchers in [3] propose a more comprehensive disease detection system. Their system tackles the problem from image acquisition or capturing the plant to classification or identifying the specific disease. This involves crucial steps like image pre-processing (cleaning and preparing the image for analysis) and feature extraction i.e. identifying key characteristics within the image. By incorporating these additional processes, the system in [3] aims to achieve not only high accuracy but also robustness in detecting and classifying a wider range of diseases, potentially beyond citrus fruits and even for different plant species.

Recent advancements in artificial intelligence (AI) are proving useful in agricultural disease detection. One study [4] explored a deep learning approach that combined the strengths of convolutional neural networks (CNNs) for image feature extraction and long short-term memory (LSTM) networks for capturing temporal information. This combination achieved an impressive 95.90% accuracy in classifying multiple guava diseases from fruit images, with Guava Canker detection reaching an even higher success rate of 98.26%. This suggests that the model could effectively learn and differentiate the visual signatures of various diseases.

In contrast, another study [5] focused on CNN architectures like VGG16 and VGG19 for a simpler classification task: differentiating healthy guava leaves from those affected by the disease. By leveraging these pre-trained CNN models, the researchers achieved a remarkable accuracy of 99.62%. This approach highlights the potential of CNNs for rapid and precise disease identification in the field, even with a less complex model structure. The paper[6] proposed image processing techniques using Gabor filter for feature extraction and artificial neural network for classification, and achieving an accuracy of 97.3%.

The paper[7] discusses image preprocessing including resizing, thresholding, and Gaussian filtering. Segmentation utilized K-means clustering, while classification employed SVM, ANN, and fusion methods for grape leaf disease detection. Fusion classifier achieved 100% accuracy for Powdery Mildew, SVM: 93.33% for Downy Mildew, 83.33% for Powdery Mildew. ANN: 86.67% for Downy Mildew, 91.67% for Powdery Mildew.

The fight against plant diseases is crucial for maintaining healthy crops and high yields. In the realm of automatic disease detection, researchers are constantly innovating. One approach utilizes multilayered convolutional neural networks (MCNNs) [8]. This powerful technique achieved an impressive 98% accuracy in classifying mango leaf diseases, demonstrating its potential for real-world applications.

Another promising method involves segmenting diseased regions from healthy leaf tissue [9]. By focusing on these specific areas, researchers can train a CNN model to classify them based on extracted features like color, texture, and shape. This approach boasts an accuracy of up to 90%, offering a valuable tool for targeted disease identification.

For situations where computational resources might be limited, traditional machine learning techniques remain viable options. Studies have explored the effectiveness of segmentation methods like K-means clustering and thresholding to isolate diseased regions [10]. These techniques are then coupled with feature extraction, analyzing color, texture, and shape variations to distinguish healthy from diseased tissues. Subsequent classification using a Support Vector Machine (SVM) has achieved accuracy levels of 88.89%, demonstrating its potential as a robust and efficient approach.

The power of machine learning extends beyond just large datasets. Research on citrus greening disease in oranges showcases the promise of this technology for smaller datasets as well [11]. By pre-grouping similar features from images using K-means clustering, followed by SVM classification for healthy/diseased categorization, researchers achieved a remarkable near-perfect accuracy, misidentifying only 2 out of 20 diseased oranges. This highlights the potential for this method in scenarios where large datasets might not be readily available.

Beyond mangoes and oranges, researchers are actively exploring applications in other crops. A study on strawberry disease detection employed a CNN model in conjunction with data augmentation techniques [12]. This process involves manipulating training data through methods like rotation, shearing, flipping, and shifting to create a more robust dataset. Utilizing the well-established ResNet-50 model, the researchers achieved a remarkable accuracy of 98.09%, demonstrating the generalizability of CNNs for various plant disease classification tasks.

The field of automated plant disease detection is rapidly evolving, with researchers exploring various machine learning techniques. One study [13] achieved promising results using a combination of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for kiwi leaf disease detection. Their model boasted high precision, recall, and F1-score, demonstrating its effectiveness in identifying diseased leaves, with an overall accuracy exceeding 83%.

In another study [14], researchers focused on mango leaf analysis. They employed digital image processing techniques to extract features like RGB values and leaf texture. K-means clustering was then applied to classify the extracted data, aiming to identify various nutrient deficiencies in the mango trees. This approach highlights the potential of unsupervised machine learning for non-disease related plant health assessments.

Furthermore, a third study [17] delved into the power of CNNs for disease pattern recognition in citrus plants. Their investigation explored the application of CNNs to automatically identify and categorize citrus diseases using image processing and machine learning. This research paves the way for the development of automated detection and remedy solutions for citrus plant health management.

The paper [18] proposes a hybrid method in optimizing automatic hybrid strategy Deep learning for plant leaf disease classification. In their method they initially perform preprocessing using image resizing and Gaussian filtering. The infected region is then segmented using UNet for getting the acquired region and enhances the disease classification accuracy. In UNet the hunter prey optimization algorithm is used. Also, a grey level co-occurrence matrix, scale-invariant feature transform and Gabor filter in extracting the features for classification, the classification is then performed using artificial driving-EfficientNet. In which their method produces a better accuracy and precession.

A Shrotriya et. al [20] they proposes an integrated clustering method and neural network for enhancing the efficiency in identifying and studying the plant disease. They identify the diseases of a plant mainly on alternaria, anthracnose, bacterial blight, and cercospora leaf spot by using CNN for feature extraction and applying clustering method in grouping the similar feature, a training set is created using multiclass support vector machine (SVM) in order to facilitate the disease identification. Table 1 illustrates all of the work done in the above papers

Table 1. Short summary of existing paper

Ref.	Methodology	Keywords	Results
[1]	SVM, CNN	Leaf Disease, Disease Detection, Image Processing, and Artificial Neural Network	89.41%
[2]	DenseNet-121	Citrus Leaves, Citrus Fruits, Deep Learning (DL), Disease Detection, Classification, DenseNet.	96%
[3]	CNN	disease detection, pre-processing, feature extraction, artificial neural network, diseases classification.	Detecting and classifying the disease in bananas.
[4]	CNN, LSTM	Guava fruit classification, Hybrid model, Crop Disease.	98.26%
[5]	CNN, VGG16, VGG19	Agriculture, Classification, CNN, Image processing, Optimization.	99.62%
[6]	Gabor filter, ANN	Coconut tree leaves, statistical features, k-means clustering, Cubic SVM	97.3%
[7]	SVM, ANN	Image Processing, Leaf diseases detection, K-means clustering, Support Vector Machine (SVM), Artificial Neural Network (ANN), Fusion Classification Technique	SVM:93.33% for Downy Mildew,83.33% for Powdery Mildew, ANN:86.67% for Downy Mildew, 91.67% for Powdery Mildew
[8]	MCNN	Agriculture, Blight Canker, Convolution Neural Network, Correlation, Mango leaves disease, Phomba Blight.	98%
[9]	CNN	Orange, Orange Leaves, computer vision, disease, SVM Classifier, GLCM, K-means	90%
[10]	K-means, SVM	Image Processing, Leaf diseases detection, K-means clustering, feature extraction, SVM Classification	88.89%
[11]	K-means, SVM	K-means clustering, Disease Grading, Fuzzy logic, Multi-Class SVM.	Out of 20 diseased oranges, 2 oranges are misidentified.
[12]	CNN, ResNet-50	Strawberry diseases, convolutional neural network, image processing, spot leaf, scorch leaf.	98.09%
[13]	CNN, SVM	Multiclassification, Leaf diseases, Kiwi fruit, Deep Learning	83.34%
[14]	K-means	Machine Learning, Agriculture, K-Means Clustering, Image Processing, Deficiency	Detect nutrient deficiencies in mango leaves.
[17]	CNN	CNN, image processing, machine learning, disease detection, citrus plants.	Identify and categorize diseases in citrus plants and providing remedy solution.

As we can see most of the existing work has proposed different ways of executing their system and producing different results. The fight against plant disease is entering a new era and great fields towards AI and ML technology for agriculture [19]. This research (referencing the studies mentioned previously) exemplifies the power of machine learning to automate disease detection. From the adaptability of Support Vector Machines (SVMs) to the sheer pattern-recognition prowess of Multi-layer Convolutional Neural Networks (MCNNs), a versatile arsenal is being built. This paves the way for earlier diagnoses, targeted interventions, and ultimately, a healthier future for our crops. The potential impact on agriculture is undeniable, promising increased yields and improved crop management strategies.

3 Methodology

This section presents the methodology that is followed, and it outlines the key steps involved in developing an automated detection of Apple and Mango Fruit and Leaf Diseases: A Machine Learning and Simple Neural Network Approach.

3.1 Data Collection

This work utilizes a comprehensive dataset comprised of photographic images depicting both healthy and diseased states of fruits and leaves. The mango dataset boasts a rich variety, encompassing diseased photos for both leaves and fruits. Specific leaf disease categories include Anthracnose, Bacterial Canker, Cutting Weevil damage, Dieback, Gall Midge infestation, Powdery Mildew, and Sooty Mold, alongside images of healthy leaves for comparison. Similarly, the mango fruit category features photos of infected fruits with Alternaria, Anthracnose, Black Mold Rot, and Stem End Rot, contrasted with healthy specimens.

The apple dataset maintains a similar structure, featuring images of diseased leaves showcasing Black Rot, Cedar Rust, Scab, and Canker, alongside healthy leaves. Additionally, the apple fruit category includes photos of Sooty Mold infection, allowing for comparative analysis with healthy apple fruits. These diverse datasets were meticulously collected from reputable online resources such as Kaggle [15, 16], ensuring a robust and well-rounded data foundation for this research.

3.2 Data Preprocessing

In the crucial stage of data preprocessing, we ensured our image data was compatible with the machine learning model. To achieve this, we performed image rescaling. This involved adjusting the pixel values of each image to reside within a standardized range of 0 to 1. This normalization was accomplished by dividing each pixel value by 255, effectively creating a consistent value scale across the entire dataset.

Furthermore, we enriched the training data using data augmentation techniques. This process involves artificially generating additional training images from the existing ones. We employed various augmentation methods including random rotations, horizontal and vertical shifts, and random zooming. These techniques help the model learn from a wider variety of image variations, improving its ability to generalize and perform well on unseen data. Finally, we implemented label encoding using a one-hot encoding scheme. This process transforms categorical labels (e.g., disease types) into a numerical representation suitable for the machine learning model. This one-hot encoding was applied to both the training and testing datasets, ensuring consistency in how labels are represented throughout the training and evaluation process.

3.3 Model

In the context of disease analysis for mangoes and apples, we implement a Simple Neural Network (SNN) algorithm, specifically utilizing transfer learning with the MobileNetV2 architecture pretrained on the ImageNet dataset. The approach involves freezing the pretrained layers of MobileNetV2 to retain learned features while incorporating custom dense layers for classification. These added layers utilize Rectified Linear Unit (ReLU) activation functions, with a softmax activation function in the final layer for multi-class classification. Through training on datasets containing images of diseased mango and apple fruits, as well as diseased mango and apple leaves, the model learns to distinguish between different diseases affecting these fruits. Evaluation metrics such as accuracy are employed to assess the model's performance. Figure 1. describes the system architecture of the proposed work.

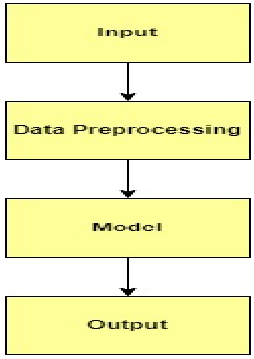

Figure 1. System Architecture

In the system architecture, the user will add a photo, then preprocessing will be performed on the image, such as image rescaling, data augmentation including random rotation, random horizontal shifts, random vertical shifts, random zoom, and fill mode. After that, label encoding will be applied, followed by analyzing the image by the model. Then, the output will display which disease is present in the image.

4 Experimental Result and Discussion

This section unveils the results yielded by the system and initiates a discussion on these outcomes.

To thoroughly evaluate the designed system's efficacy in real-world scenarios, we utilized a comprehensive dataset containing 4862 images. This dataset was strategically split, with 3646 images dedicated to the training phase. During this crucial stage, the model was exposed to a wide variety of healthy and diseased plant samples, enabling it to learn and refine its ability to distinguish between the two. The remaining 1216 images were reserved for the testing phase. Here, the model's performance was assessed on unseen data, providing a more objective measure of its generalizability. This rigorous approach yielded impressive results, with the model achieving a remarkable 95% accuracy rate. This high accuracy signifies the model's exceptional capability to accurately classify healthy and diseased plant instances within the dataset. Below we briefly discuss the achieved result from the proposed model. In order to check how the designed system works, we have given a diseased photo of a mango and a leaf as input. The sample input image is shown in Figure 2, and Figure 3.

Figure 2. Sample Blight Mango fruits **Figure 3.** Sample sick Mango leaf

The image in Figure 2 and 3 clearly shows signs of spoilage and disease on a mango and a leaf as well. While human observation can identify these issues to some extent, accurately pinpointing the specific disease type can be challenging. This is where our designed system comes in. By learning from a vast dataset of labeled mango leaf images with different diseases, the system is equipped to analyze images and classify it's diseases or illness.

Following the pre-processing techniques as discussed earlier, a sample pre-processed mango disease image is presented in Figure 4.

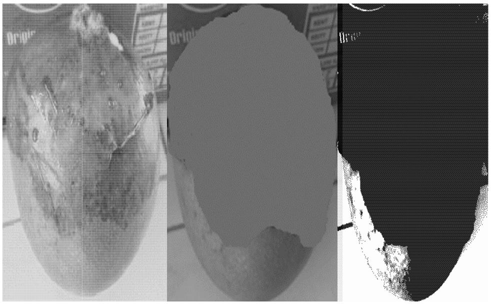

Figure 4. Some pre-processing view on the mango image.

As illustrated in Figures 4 and 5, the designed system takes the input image (like the one in Figure 3) and outputs the identified disease name. This demonstrates the system's ability to learn from training data and perform accurate disease classification, which is a valuable tool for early detection and intervention in mango crops.

Figure 5. Sickly Mango leaflet **Figure 6.** Diagnosed Mango leaflet

Training and validating data visualization is presented in Figure 7, the graph depicts the learning journey of a model over time. We can observe a distinct pattern in its performance on both the training and validation datasets. Initially, the training accuracy exhibits a steady climb. This signifies the model's successful absorption of knowledge from the training data. However, the validation accuracy lags behind, failing to keep pace with this rapid improvement. This discrepancy highlights a phenomenon known as overfitting. Overfitting occurs when a model prioritizes memorizing the specifics of the training data, including noise and irrelevant details, rather than capturing the underlying generalizable patterns. This over-specialization leads to a significant gap between the training and validation accuracies.

As the training progresses, the validation accuracy demonstrates a gradual upward trend, eventually starting to catch up with the training accuracy. This convergence point marks a crucial shift in the model's learning process. It signifies that the model's capacity to extract generalizable knowledge from the data has surpassed its tendency to memorize noise. This ability to learn transferable patterns is paramount for a model's success in real-world applications, where it will encounter entirely unseen data.

Following convergence, both the training and validation accuracies stabilize, reaching a plateau. This plateau signifies that the model has reached a point of diminishing returns. It has extracted as much valuable knowledge as possible from the available data without succumbing to overfitting. This stable performance on the validation data, depicted in Figure 6, instills confidence in the model's ability to generalize well to unseen data. In essence, the model is now equipped to perform reliably in real-world scenarios.

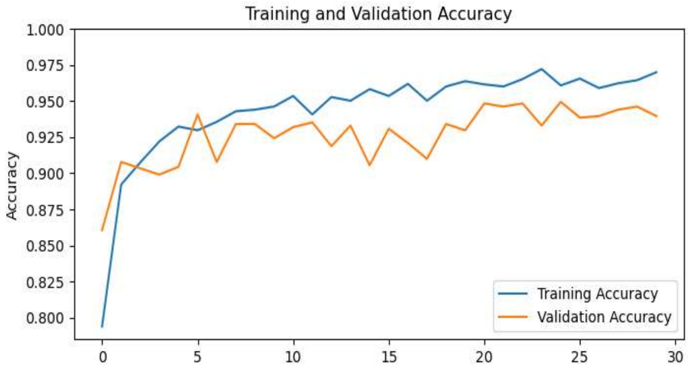

Figure 7. Training vs Validation Accuracy

5 Conclusion

This research demonstrates the potential of machine learning and neural networks to empower farmers with a fast, accurate, and user-friendly system for disease detection in apple and mango crops. Achieving a 95% success rate in controlled settings highlights the effectiveness of this approach. Furthermore, its inherent flexibility suggests broad applicability across diverse farm sizes and locations. The adoption of this technology has the potential to revolutionize agricultural practices, promoting smarter farming methods and ultimately contributing to a more secure food supply.

While the current study lays a promising and simple state-of-art system execution. further validation and optimization of these automated disease detection methods are necessary. Future research should focus on evaluating their efficacy in real-world agricultural environments encompassing diverse regions and growing conditions. Additionally, integrating environmental data (e.g., weather patterns) and potentially even genetic information about the crops could lead to more robust disease prediction and management strategies. Beyond technical advancements, exploring the socioeconomic implications of adopting such automated systems is crucial. This includes understanding their potential impact on farmer livelihoods, resource allocation decisions, and potential barriers to widespread adoption. By fostering interdisciplinary research efforts that bridge these technical and social aspects, we can pave the way for the successful global implementation of automated disease detection technologies in agriculture.

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