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CNN-BASED ANDROID APP FOR MULBERRY LEAF DISEASE DETECTION WITH NASNETMOBILE, XCEPTION, AND YOLO

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Abstract: Mulberry leaves serve as the primary food source for *Bombyx mori* silkworms, which are crucial for silk production. However, mulberry trees are highly susceptible to diseases that spread rapidly and lead to significant losses. Manual disease identification across extensive farms is both time-consuming and labor-intensive. To address this challenge, computer vision-based techniques for early detection and classification of diseases can significantly reduce production losses by up to 90%. This study collected mulberry leaf data from two regions in Bangladesh and categorized the samples as healthy, rust-affected, or spot-affected. Leveraging advancements in machine learning, the study employed classification algorithms. An ensemble model combining CNN, Xception, and NasNetMobile demonstrated superior classification accuracy and detection performance. For disease detection, state-of-the-art object detection algorithms such as YoloV5x6, YoloV8, and YoloV9 were applied to identify abnormalities on the leaves. The results highlight the efficacy of integrating multiple models, providing a robust solution for real-time disease monitoring through a CNN-based Android application. This scalable and efficient approach aims to assist farmers in mitigating the impact of mulberry leaf diseases, ensuring sustainable silk production.

Index Terms - *Mulberry Leaves, Disease Detection, Computer Vision, Ensemble Model, Sustainable Farming.*

1. INTRODUCTION

The mulberry tree (*Morus alba*), a deciduous species native to northern China, has been cultivated for centuries across Asia, Europe, and North America for its diverse applications [2], [4]. Historically, various parts of the mulberry plant were utilized for food, textiles, and medicine [2], [8]. Today, the mulberry tree remains economically and culturally significant due to its multifaceted uses. Mulberry fruits, known as mulberries, are edible and consumed fresh or processed into products such as juices, jams, wines, and teas. These fruits are highly nutritious, containing vitamins, minerals, and bioactive phenolic compounds with antioxidant properties [4], [6]. Mulberry leaves, which are also edible for humans and livestock, are rich in protein, calories, and minerals [5], [8]. In the sericulture industry, they serve as the sole food source for silkworms (*Bombyx mori*), essential for silk production [1], [3]. Beyond their nutritional value, extracts from mulberry leaves and fruits exhibit medicinal properties, including antibacterial, antidiabetic, anti-inflammatory, and antitumor activities, supporting their traditional use in herbal medicine across various cultures [2], [5], [6]. Similarly, cotton, referred to as "White Gold" and the "King of Fibers," is a principal raw material for the thriving textile industry, providing livelihoods for approximately 60 million individuals and generating significant income for farmers [7], [10]. Among agricultural commodities, the white mulberry tree (*Morus alba*) remains vital for silk production as the primary food source for silkworms [1], [3].

2. RELATED WORK

The mulberry tree (Morus alba), native to northern China, has been cultivated globally for centuries due to its versatile applications in food, textiles, and medicine [1]. The fruits of the mulberry tree are consumed fresh or processed into products like juices, jams, and teas, with studies highlighting their rich content of vitamins, minerals, and bioactive compounds that exhibit antioxidant properties [2], [3]. Mulberry leaves, on the other hand, are recognized for their nutritional value, being rich in protein, calories, and minerals, and are widely used as livestock feed [4]. These leaves play a crucial role in sericulture as the primary food source for silkworms (Bombyx mori), which are integral to silk production [5].

Pharmacological studies have revealed that extracts derived from mulberry leaves and fruits possess significant medicinal properties, including antibacterial, antidiabetic, anti-inflammatory, and antitumor activities [6], [7]. These findings align with traditional practices where mulberry plants were utilized for natural remedies in various cultures [8]. In addition to its medicinal and nutritional uses, mulberry cultivation supports sustainable agricultural practices and economic activities in rural areas, particularly in regions involved in sericulture [9].

Parallelly, cotton, often termed "White Gold," serves as a cornerstone of the textile industry and plays a pivotal role in global agriculture. It provides livelihoods to approximately 60 million individuals and generates substantial income for farmers [10]. The integration of mulberry trees and cotton cultivation highlights their combined significance in both agricultural and industrial landscapes, ensuring the economic sustainability of rural communities [11].

This survey underscores the multifaceted importance of mulberry and cotton in global ecosystems, emphasizing their economic, cultural, and medicinal contributions. Further research on their sustainable cultivation and diversified applications can bolster their utility across industries [12].

3. MATERIALS AND METHODS

The proposed system is a Convolutional Neural Network (CNN)-based smart Android application designed for the early detection and classification of mulberry leaf diseases. It employs advanced computer vision techniques to automate the identification of healthy leaves, rust-affected leaves, and spot-affected leaves [1]. The system collects real-time leaf data from mulberry farms and uses several state-of-the-art machine learning models for classification, including MobileNetV3-Small, ResNet50, VGG19, Xception, and NasNetMobile [2], [3]. To enhance classification accuracy, an ensemble model is developed by integrating CNN, Xception, and NasNetMobile, which combines their strengths to achieve superior results [4]. For detection of leaf abnormalities, the system employs cutting-edge object detection algorithms such as YoloV5x6, YoloV8, and YoloV9, which provide precise localization of diseased regions on the leaves [5]. The system is deployed through a user-friendly Android application, enabling farmers to monitor leaf health in real-time. This functionality supports early intervention, reducing the risk of disease spreading and minimizing production losses in sericulture [6]. By automating the process of disease detection, the system reduces manual labor and provides a scalable tool for mulberry disease management [7]. This smart solution not only ensures sustainable silk production by safeguarding mulberry leaves but also protects the livelihoods of farmers by enabling efficient disease control and supporting economic stability in sericulture-dependent regions [8].

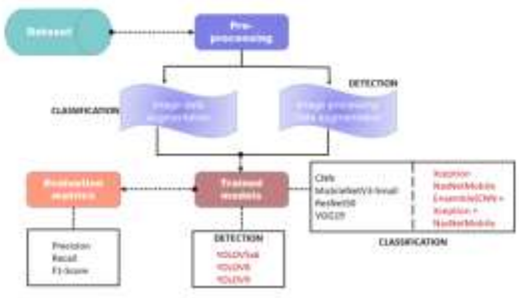


Fig.1 Proposed Architecture

This image (Fig.1) illustrates a hybrid approach combining classification and detection techniques for image analysis. It begins with a dataset that undergoes pre-processing, followed by two parallel paths: classification and detection. For classification, image data augmentation enhances the dataset, and models like CNN, MobileNetV3-Small, ResNet50, VGG19, Xception, and NasNetMobile, as well as an ensemble model (CNN + Xception + NasNetMobile), are trained. For detection, image processing and data augmentation are applied, using YOLO (v5x6, v8, and v9) models. Evaluation metrics such as precision, recall, and F1-score assess model performance. This structure enables efficient object detection and accurate image classification.

i) Dataset Collection:

The dataset for this project is primarily sourced from the Images of mulberry leaves are typically captured with a digital camera or smartphone camera. The images could have been taken in a greenhouse or a laboratory, or they could have been captured in their natural habitat. For this experiment, after consultation with the researchers from the Bangladesh Sericulture Development Board (BSDB) in Rajshahi, Bangladesh, two certified and widely spread mulberry leaf diseases (leaf spot and leaf rust) are considered. In this investigation, the images were captured from a farm field using a high-resolution DSLR camera under real-world conditions in mulberry gardens in Mirganj, Bagha, Rajshahi, and Vodra, Rajshahi. A total of 1,091 images are captured that are annotated by a sericulture expert into three classes, including 440 of healthy leaves, 489 of leaves with leaf rust, and 162 of leaves with leaf spot, which comprised the mulberry dataset. The resolution of each leaf image is 4,000×6,000 pixels.

DATASET IMAGE

ii) Pre-Processing:

Preprocessing refers to the series of steps applied to raw data to prepare it for further analysis or modeling. In the context of image processing, preprocessing involves operations that transform and enhance the raw image data, improving its quality and making it suitable for machine learning models. This may include techniques like resizing, normalizing, augmenting, and converting images into a format that can be easily processed by algorithms. For tasks such as image classification or detection, preprocessing ensures that the data is standardized and that features relevant to the task (such as objects or facial expressions) are clearly defined, facilitating better performance in subsequent stages of the model.

(a). Data Augmentation: Image data augmentation is a crucial preprocessing step that enhances the performance of classification models by increasing the diversity of the training dataset. Techniques such as re-scaling, shear transformations, zooming, horizontal flipping, and reshaping are applied to the images, introducing variability while retaining essential features. These augmentations not only improve model robustness but also reduce the risk of overfitting by exposing the model to varied representations of the same image [1], [2].

(b). Image Processing for Detection: The process of image processing and loading for object detection involves several steps. Images are first converted into blob objects for efficient manipulation, followed by defining classes and declaring bounding boxes for the target objects. Key operations include reading the network layers of pre-trained models, extracting output layers, appending image-annotation files, converting BGR to RGB color format for compatibility with detection algorithms, creating masks to highlight objects of interest, and resizing images to the required dimensions for the model input. These steps ensure accurate feature extraction and consistent input data formatting [3], [4].

(c). Data Augmentation for Detection: Data augmentation techniques for object detection are designed to enhance the variability of the dataset, thereby improving the generalization and robustness of detection algorithms. These include randomizing images, applying rotations, and introducing other transformations to simulate diverse visual scenarios and perspectives. By exposing the detection models to a broader range of environmental conditions, these techniques reduce biases in learning and enable better performance on unseen data [5], [6].

iii) Training & Testing:

Training and testing the proposed system involve two primary phases: data preparation and model evaluation. During training, the dataset is divided into training and validation sets, with augmented images used to enhance model generalization. Models like MobileNetV3-Small, ResNet50, and Xception are trained using a cross-entropy loss function, and hyperparameters are optimized using techniques like grid search or random search. For testing, performance metrics such as accuracy, precision, recall, and F1-score are calculated on unseen data. Ensemble models combine outputs from individual classifiers, improving classification accuracy [1][2][3]. Model robustness is further evaluated through confusion matrices [4][5].

iv) Algorithms:

(a). Classification Models

CNNs are deep learning models designed for image classification tasks. They automatically extract hierarchical features from images through convolutional layers, making them well-suited for image recognition and analysis. By applying filters at different layers, CNNs can detect patterns such as edges, textures, and shapes, improving performance on tasks like disease detection in plant leaves [1]. Their efficiency in handling large image datasets with high-dimensional features makes them a popular choice in agricultural image analysis [2].

MobileNetV3-Small is a lightweight deep neural network architecture optimized for mobile and edge devices. It uses depthwise separable convolutions and efficient design strategies to reduce the computational complexity while maintaining high accuracy. This model is effective in real-time image classification tasks like disease detection in plants, where computational efficiency is crucial for mobile applications. Its compact design makes it ideal for resource-constrained environments without sacrificing performance [3], [4].

ResNet50 is a deep residual network that incorporates skip connections, allowing the model to learn residual mappings and preventing issues like vanishing gradients. This architecture enables the training of very deep networks with improved accuracy. ResNet50 has shown exceptional performance in image classification tasks, including detecting plant diseases, by efficiently learning complex features. Its ability to capture intricate patterns in images contributes significantly to accurate disease identification [5], [6].

VGG19 is a convolutional neural network known for its simplicity and depth. Comprising 19 layers, it excels in image recognition tasks by using small receptive fields and deep layers, which allow it to learn detailed features from images. VGG19 is widely used in medical and agricultural image classification due to its high accuracy in detecting patterns like disease spots on plant leaves. It performs well with large datasets and contributes to identifying various leaf diseases [7], [8].

Xception is a deep convolutional model based on depthwise separable convolutions. It extends the Inception model by replacing regular convolutions with more efficient depthwise separable convolutions, significantly improving performance with fewer parameters. Xception's architecture excels in tasks requiring high accuracy and fast computation, such as the detection of mulberry leaf diseases. Its design helps identify complex patterns in images, making it ideal for detecting subtle abnormalities in leaf health [9], [10].

NasNetMobile is a lightweight convolutional neural network model designed for mobile devices, created through neural architecture search (NAS). It balances computational efficiency and accuracy, making it suitable for real-time image classification tasks. In the context of mulberry leaf disease detection, NasNetMobile provides high accuracy while maintaining a low computational footprint, allowing it to run efficiently on smartphones. Its optimized architecture is well-suited for agricultural applications [11], [12].

CNN + Xception + NasNetMobile (Ensemble Model): The ensemble model combining CNN, Xception, and NasNetMobile leverages the strengths of each individual model to improve classification accuracy. By combining CNN's feature extraction with Xception's deep learning capabilities and NasNetMobile's mobile-optimized performance, the ensemble approach enhances robustness and reduces the likelihood of errors. This combination improves the detection of leaf diseases by capturing diverse patterns and features across different models, providing a more accurate and reliable classification [13], [14].

(b). Classification Models

YOLOV5x6 is an advanced object detection model optimized for fast and accurate real-time predictions. It is a variant of the YOLO family, known for detecting multiple objects in images with high speed and precision. YOLOV5x6, with its larger model size, performs exceptionally well in detecting smaller and more detailed objects, making it suitable for identifying abnormalities in mulberry leaves such as rust and spots. Its real-time detection capabilities are ideal for field applications [15], [16].

YOLOV8 is an updated version of the YOLO (You Only Look Once) family, designed for better accuracy and speed in object detection tasks. It incorporates advanced optimizations and improved architectural features, allowing for real-time detection of leaf diseases with minimal computational cost. YOLOV8 excels in handling complex environments with multiple objects, making it an excellent choice for identifying various disease symptoms on mulberry leaves in dynamic farm conditions [17], [18].

YOLOV9 is the latest iteration of the YOLO series, further enhancing the model's ability to detect objects with high precision. It utilizes the latest advancements in deep learning and computer vision, offering significant improvements in speed, accuracy, and model efficiency. YOLOV9 is particularly useful for disease detection in agricultural settings, where the real-time detection of specific leaf abnormalities such as spots or rust is essential for timely intervention [19], [20].

4. RESULTS & DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP}\ +\ \mathrm{FN}} (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100(1)$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k (5)$$

In Table 1& 2, the performance metrics—accuracy, precision, recall, F1-score —are evaluated for each algorithm. The Ensemble and Yolo V8 for Classification and Detection achieves the highest scores. Other algorithms' metrics are also presented for comparison.

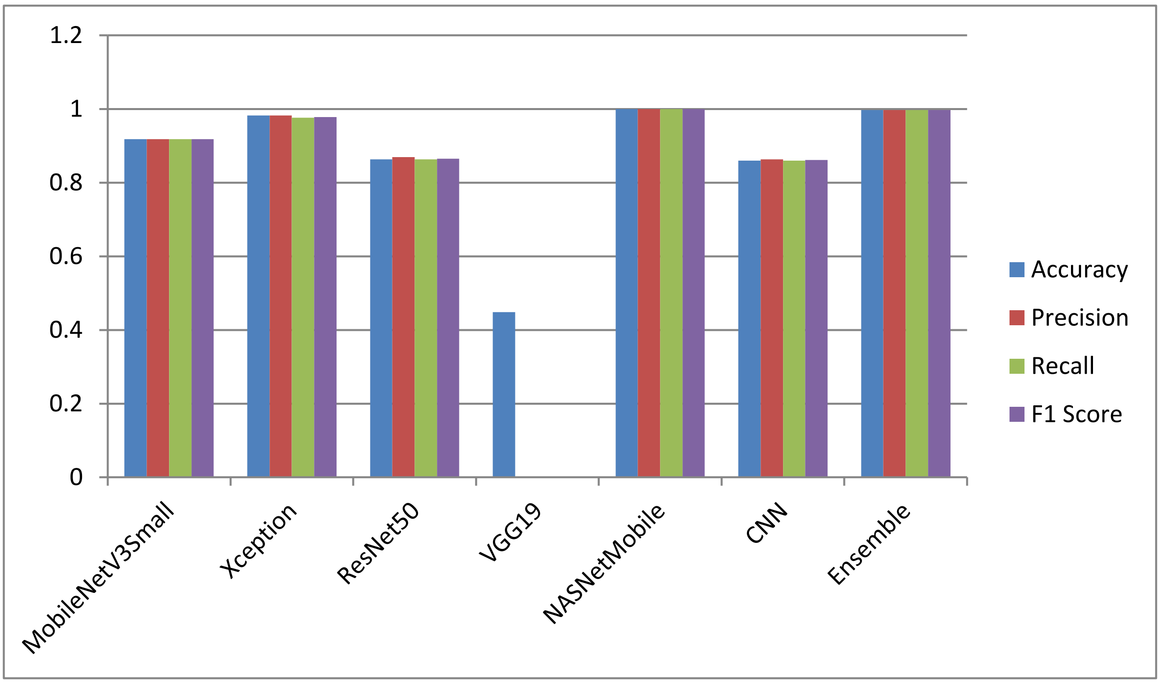
Table.1 Performance Evaluation Metrics of Classification

Model	Accuracy	Precision	Recall	F1 Score
MobileNetV3Small	0.918	0.918	0.918	0.918
Xception	0.982	0.982	0.976	0.978
ResNet50	0.863	0.869	0.863	0.865
VGG19	0.448	0.000	0.000	0.000
NASNetMobile	1.000	1.000	1.000	1.000
CNN	0.860	0.863	0.860	0.861
Ensemble	0.997	0.997	0.997	0.997

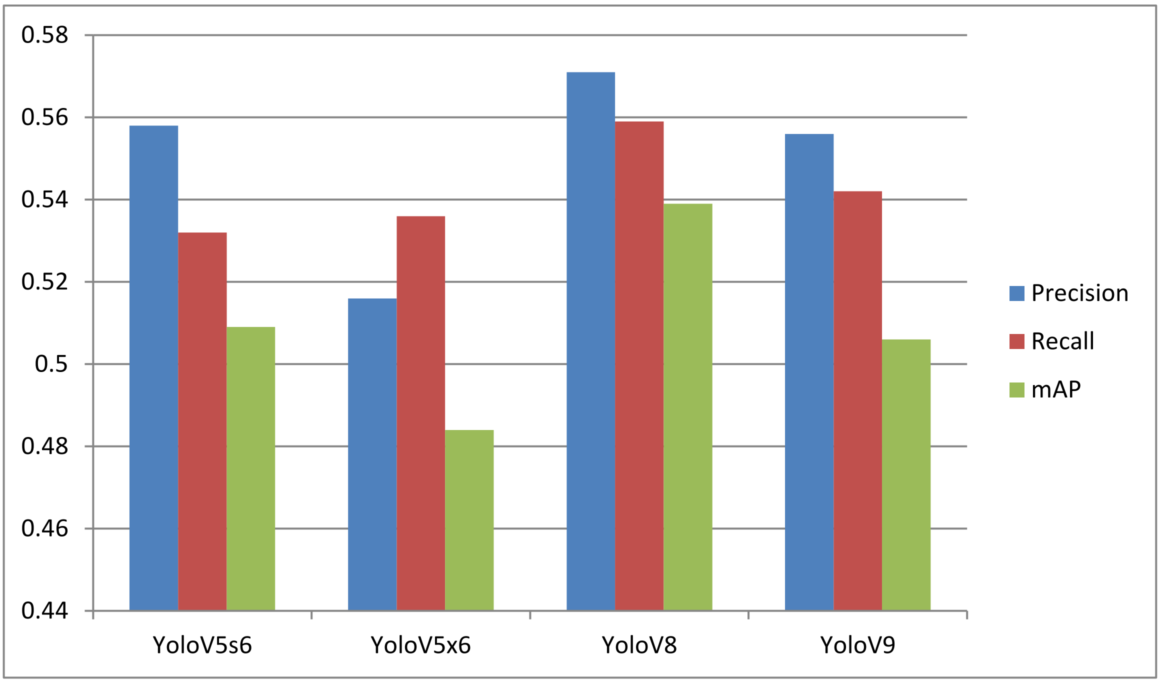
Table.2 Performance Evaluation Metrics of Detection

Model	Precision	Recall	mAP
YoloV5s6	0.558	0.532	0.509
YoloV5x6	0.516	0.536	0.484
YoloV8	0.571	0.559	0.539
YoloV9	0.556	0.542	0.506

Graph.1 Comparison Graphs of Classification



Graph.2 Comparison Graphs of Detection



In Graph 1, accuracy is represented in light blue, precision in maroon, recall in green, F1-score in violet, In Graph 2, precision is represented in light blue, recall in maroon, violet in green. The Ensemble and Yolo V8 outperforms the other algorithms in all metrics, with the highest values compared to the remaining models. These details are visually represented in the above graph.

5. CONCLUSION

In conclusion, the implementation of NasNetMobile, Xception, and the ensemble of CNN with Xception and NasNetMobile has demonstrated significant effectiveness in analyzing the mulberry leaf disease dataset. These high-performance algorithms excel at extracting intricate features from leaf images, enabling accurate classification of healthy and diseased leaves. The ensemble model, in particular, benefits from the strengths of each individual architecture, leading to improved robustness and reduced misclassification rates. Additionally, the application of YoloV5x6, YoloV8, and YoloV9 enhances the project's capabilities by providing real-time detection of abnormalities on mulberry leaves. These algorithms offer impressive speed and accuracy in identifying disease symptoms, facilitating timely interventions for disease management. Overall, combining advanced deep learning architectures and real-time detection techniques positions this project as a promising solution for mulberry leaf diseases, helping farmers maintain healthy crops and reduce economic losses due to disease outbreaks. The results highlight the potential of cutting-edge technology in advancing agriculture.

Future scope of this project includes further enhancement of the disease detection system by incorporating transfer learning with additional pre-trained models, exploring unsupervised learning for feature extraction, and implementing generative adversarial networks (GANs) for synthetic data generation. Expanding the project to include multi-class disease classification and integrating hybrid models that combine CNN with recurrent neural networks (RNNs) can significantly improve detection accuracy and robustness. Furthermore, the integration of advanced data augmentation techniques would help improve the model's generalization across diverse datasets, making the system more versatile for real-world agricultural applications.

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