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A Hybrid Machine Learning Approach Utilizing CNN Feature Extraction with Traditional Classifier to Identify Strawberry Leaf Diseases

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***Abstract*—Strawberry production is globally significant because it contains high nutrients. Strawberry leaf disease shapes a significant barrier to strawberry cultivation worldwide. Numerous strawberry leaf diseases can impede the growth of strawberry plants. Leaf Scorch is one of the dangerous strawberry leaf diseases caused by the fungus "Diplocarpon Earliana." Strawberry leaf disease diagnosis by traditional methods requires a lot of effort and time and is also challenging to identify accurately. In order to increase strawberry production, it is therefore essential to automatically detect strawberry leaf diseases. Machine learning and Deep learning have the potential to detect strawberry leaf diseases automatically. In this paper, we proposed a hybrid Machine Learning methodology using CNN feature extraction with the traditional ML classifier to detect Strawberry Leaf Diseases. For this instance, we used the strawberry leaf dataset from the PlantVillage Updated dataset. Based on our research, ResNet50 with Support Vector Machine diagnoses strawberry leaf scorch with 99.80% accuracy. This research assured sustainable advancements in strawberry production by integrating and offering an effective way to detect strawberry leaf diseases.**

***Index Terms*—Deep learning, Machine Learning, Convolutional Neural Network, Feature Extraction, Hybrid Model, Strawberry leaf disease.**

I. Introduction

Strawberry is a widely beloved fruit, not just for its taste but also for its high concentration of nutrients that are beneficial for humans including vitamin C, folate, and phenolic compounds [1]. According to traditional Chinese medicine, the strawberry is an alkaline fruit that helps relieve heat, satisfy thirst, and coughs. It is also very good for nourishing the lungs and blood. Apart from their health benefits, strawberries are a valuable commodity in the global economy, with an annual production of around 9 million tons [2].

Strawberry is a widely consumed berry and one of the most preferred fresh fruits. It is a fruit crop with substantial economic significance. More than seventy nations produce strawberries commercially [3]. Strawberry cultivation is becoming popular in Bangladesh, which is in line with the world, and overall annual production is steadily rising in Bangladesh. According to the business standard, 10,000 acres of land are used to cultivate strawberries in Bangladesh per year [4]. But a quiet menace waits among the rolling fields and busy marketplaces: Strawberry leaf diseases.

Strawberry leaves are often affected by fungal diseases, which creates significant concern. The most known diseases include angular leaf spot, leaf scorch, leaf blight, leaf spot, blossom blight, gray mold, and powdery mildew [5]. These diseases have a devastating impact on a nation's economy. So, the identification of the disease at an early stage can be beneficial for farmers around the world and economically profitable for a nation.

Machine learning and deep learning are promising for technological progress in challenging agricultural situations. Diverse ML and DL methods and models have been developed and are available to detect disease in strawberry leaves. In this paper, we have proposed a hybrid model utilizing CNN feature extraction with traditional machine learning classifiers to identify strawberry leaf scorch early and defeat these threats. The following is our significant contribution.

- We unveiled a more robust and comprehensive approach combining Convolutional Neural Networks and machine learning methods to identify strawberry leaf diseases.
- We used convolutional neural network architectures such as VGG16, EfficientNetV2B0, MobileNetV3, and ResNet50 to extract features from image data.
- Traditional machine learning classifiers like Support Vector Machine, Random Forest, and Decision Tree were utilized to detect strawberry leaf diseases.

The headings that follow indicate the remaining sections of our research. Chapter II: Related Work - We provide an overview of the studies and surveys that are currently accessible on the identification of strawberry leaf diseases. Chapter III: Proposed Methodology - This part explains the requirements, related diagrams, and system architecture. Chapter IV: Results and Discussion - This section includes information, tables, graphs, charts, and photographs of the tools used, as well as an explanation of the machine learning models used. Chapter V: Conclusion and Future Work - the basic idea of the work is summarized, and possible future applications are discussed in this section.

II. Related Work

Many previous research has examined the application of machine learning and deep learning algorithms to the early identification of a range of plant illnesses, such as leaf diseases in apples, grasps, cherries, corn, tomatoes, potatoes, and many more. Notable endeavors have been made to tackle challenges unique to strawberries. However, it is still seen as inadequate and is one field of study currently being researched. a lack of access to healthcare and inadequate

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infrastructure exacerbates risks. *S. Karki et al.* [6] proposed the use of transfer learning in deep CNN and used models that had already been trained on the ImageNet dataset, such as the Inception V3, VGG19, DenseNet121, and ResNet50 architectures. Then, transfer learning was utilized to fine-tune and extract features from these models. The investigation results showed that, in all three configurations, Resnet-50 consistently produced the best accuracy, peaking at 94.4%. However, due to generalization issues this might not apply to all environments. *V. Gautam et al.* [7] suggested using FFIR - Feature Fusion with Inception-RestNet, a feature fusion-based deep learning model, to identify strawberry leaf diseases. A combination of the Inception-RestNet model was used to extract the features. Canonical correlation analysis (CCA) is then utilized to fuse the retrieved features in a fusion matrix. A convolutional neural network was then utilized to carry out the categorization. The suggested model fared better, with a 99.34% accuracy rate. This model relies on skilled personnel for initial disease identification. Generalization issues may arise. *Archana Saini et al.* [8] employed CNN models to automatically and reliably diagnose illnesses of strawberry leaves based on the visual symptoms gathered from image data. With a value of 0.0400 in the training phase and 0.0601 in the validation phase, epoch 15 of the MobileNetV2-based StrawDet model, built to classify strawberry leaf diseases, shows the least loss. Furthermore, it has been noted that the testing phase reaches 97.55% accuracy, while the training phase obtains a maximum accuracy of 99.21%. However, this model has scalability issues and High time complexity in early detection. *Jianping wang et al.* [9] proposed BerryNet-Lite, a lightweight network for accurate disease detection in strawberries. An attention mechanism module, which is an efficient channel attention (ECA), was used. Also, a multi-layer perceptron (MLP) module was included to improve the abstract feature capture and generalization capabilities. Lastly, a new method for designing classification heads successfully integrating the MLP and ECA modules was introduced. Based on experimental data, BerryNet-Lite achieved a remarkable 99.45% accuracy. BerryNet-Lite performs better metrics than traditional networks such as ResNet34, VGG16, and AlexNet. This model may require expert to detect strawberry leaf diseases. *Deperias Kerre et al.* [10] proposed a deep CNN model that can simultaneously identify Strawberry Leaf Spot and diseases. The model was trained and assessed using a dataset of 1134 images. The model's 98% accuracy rate shows that this strategy is feasible. The CNN model's performance was compared to that of many other ML methods, such as the RF, KNN, and SVM and three CNN architectures, GoogleNet, Resnet, and VGGNet, were also compared. However, limited data size may affect Generalization. *Rahul Singh et al.* [11] used the application of pre-trained neural networks with Transfer Learning Models to detect diseases on strawberry leaves. Specifically, the goal is to fine-tune models like MobilNetV2, EfficientNetB0, and ResNet18, which have respectively an accuracy of 80%, 99%, and 64%; the EfficientNetB0 model achieved an astounding 99% accuracy. *Jiayi Wu et al.* [12] proposed a novel DL-driven architecture for strawberry leaf illness diagnosis. Their method integrates sensor data collection and plant picture capture into a comprehensive embedded electronic system. This study presented a novel model called ResNet9-SE, a modified version of the ResNet architecture with two strategically placed Squeeze-and-Excitation (SE) blocks to improve network performance. Results from the experiments showed that the ResNet9-SE model has an outstanding 99.7% classification accuracy.

III. Proposed Methodology

The approach used to create the suggested hybrid model to identify strawberry leaf disease is shown in Fig 2, which includes its architecture, dataset preprocessing, feature extraction, building model, and training procedure. We go over each phase of the proposal in the sections that follow.

A. Data Acquisition

Data engaged in this study to detect strawberry leaf disease was collected from a public source named Kaggle. The name of the dataset is PlantVillage Updated dataset [13]. The dataset consists of total 4498 images with the specific segment, 3598 images for training, 307 for testing, and 593 for validation, respectively shown in Table I. Moreover, every segment consists of healthy and leaf scorch images. From the total number of images, 2280 were healthy, and the rest were leaf scorch. A sample of healthy and leaf scorch images is in Fig. 1.

(a) Healthy (b) Leaf Scorch

Fig. 1. Sample Strawberry Leaves of Healthy and Leaf Scorch

TABLE I
PlantVillage Updated Dataset

Class	Training	Testing	Validation	Total
Healthy	1824	154	302	2280
Leaf Scorch	1774	153	291	2218

B. Data preprocessing

Data preprocessing is essential to build a Machine Learning model because the images might contain noise. To achieve high training accuracy, removing the noisy data from the dataset using preprocessing approaches is crucial. Because training a convolutional neural network directly with raw images may lead to subpar classification results, preprocessing is essential for boosting efficiency. Prior to the photographs being entered into the model, several preprocessing methods have been applied. The pre-processing procedures used in this study include resizing, rescaling. Images with consistent sizes are needed as input for Convolutional Neural Networks. As a result, every picture inside the dataset was scaled to have consistent dimensions of 224 by 224 pixels. The process of

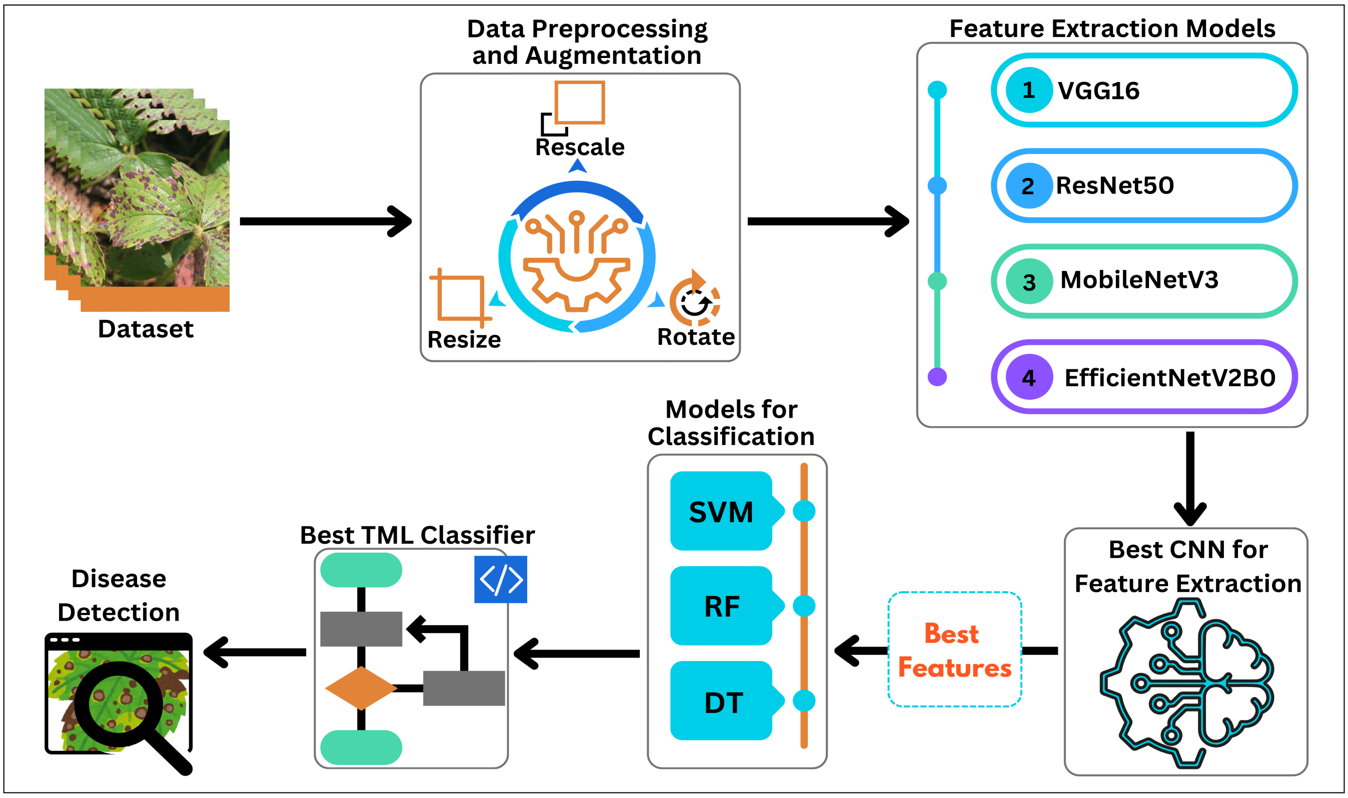

Fig. 2. Proposed Architecture for Strawberry Leaf Disease Detection

rescaling is applied after resizing, and it involves reducing the original pixel values from 0 to 224 to a range of 0 to 1.

C. Data Augmentation

Data augmentation, the process of artificially producing new data from existing data, is mostly utilized to train new machine learning and deep learning models. Data augmentation strategies are generally used to improve the model's generalization abilities and diversify the dataset [14]. By applying changes like rotation, flipping, scaling, and cropping, these methods create new pictures from the preexisting dataset. Adding additional data makes the model more robust and less prone to overfitting, eventually improving how well it performs on unseen data.

D. Feature Extraction

Effective feature extraction from image data is essential for precise classification in the context of strawberry leaf disease detection. Several deep-learning models were utilized as feature extractors in order to extract reliable and distinct characteristics from the images. The models ResNet50, MobileNetV3, VGG16, and EfficientNetV2B0 are employed for feature extraction. The unique architectures of each of these models help to extract various attributes from the collection of images. The pre-trained CNN models were fed the strawberry leaf images to extract the feature maps from the final convolutional layer for each model. After being flattened, these feature maps, which stand for high-level picture descriptors, were utilized as input features for further categorization. This procedure ensured that the most crucial information needed to differentiate between healthy and infected strawberry leaves was kept in the extracted characteristics.

1) VGG16: A popular convolutional neural network model for applications involving feature extraction and image categorization is VGG16. It has 16 layers, consisting of 3 fully connected levels after 13 convolutional layers. VGG16 uses small 3x3 convolutional filters with a set stride and padding to assist in capturing complex patterns in the picture. The rich design of VGG16 allows it to learn hierarchical characteristics, from basic edges to intricate textures [15]. In this work, we kept the convolutional basis of the pre-trained VGG16 model and removed the fully connected layers to extract deep information from photos of strawberry leaves.

2) ResNet50: The vanishing gradient issue in deep networks is addressed by ResNet50, a variation of the Residual Network - ResNet family, which adds residual learning. Batch normalization, identity skip connections, and convolutional layers are among the 50 layers that make up ResNet50. These layers provide more fluid gradient flow during backpropagation. By using skip connections, deeper networks are trained without experiencing performance deterioration [16]. We employed the pre-trained ResNet50 model for feature extraction, taking advantage of its residual blocks to extract fine-grained spatial characteristics from the images of strawberry leaves.

3) EfficientNetV2B0: The EfficientNet family has been enhanced with EfficientNetV2B0, which aims to be accurate and efficient. It combines compound scaling and unique architecture improvements to provide state-of-the-art performance on picture classification benchmarks. To improve feature extraction capabilities, it uses a variety of strategies, including multi-head self-attention and squeeze-and-excitation blocks [17]. This work focused on efficiency and efficacy by utilizing

EfficientNetV2B0 as a feature extractor to produce high-quality feature representations from images of strawberry leaves.

4) MobileNetV3: A lightweight CNN model designed for embedded and mobile vision applications is called MobileNetV3. Squeeze-and-excitation modules, inverted residual blocks, and depthwise separable convolutions are employed to strike a compromise between computing economy and accuracy. With its low resource requirements, MobileNetV3 is engineered to perform very well in feature extraction activities [18]. We used MobileNetV3 to extract characteristics from the photos of strawberry leaves since it works well when processing power is limited.

E. Image Classification

This stage entailed classifying the photos of strawberry leaves as healthy or unhealthy using conventional machine-learning classifiers after extracting features using the previously discussed deep-learning models. We utilized three widely used classifiers: Random Forest, and Support Vector Machine, Decision Tree. Every classifier functions differently regarding decision limits and generalization, and each has advantages of its own [19]. The deep feature vectors from the VGG16, ResNet50, EfficientNetV2B0, and MobileNetV3 models were fed into the SVM, RF, and DT classifiers as part of the overall classification process. To find the best feature extraction model and classifier combination for strawberry leaf disease detection, the performance of each model was assessed using several performance matrices.

1) Support Vector Machine: SVM is a supervised learning approach utilized to solve classification issues. The goal of SVM is to locate the best hyperplane in the feature space to optimize the margin between classes. An SVM classifier was used in our work to process the characteristics that were taken out of the deep learning models. The SVM is appropriate for our goal since it performs well with high-dimensional data and when the feature space is not linearly separable.

2) Random Forest: RF is an ensemble ML algorithm primarily used for regression and classification tasks. RF builds several decision trees during training. It generates a class that is either the individual tree's method of classification or mean prediction (regression). A random subset of the data trains each tree in the random forest to increase generalization and decrease overfitting. It was used in this study to categorize the features retrieved from the deep learning models because RF can handle high-dimensional feature spaces and offers resilience against overfitting.

3) Decission Tree: A straightforward yet effective classifier, Decision Tree employs a tree-like graph of decisions and their potential outcomes. The dataset is divided according to feature values, and the tree is constructed recursively from top to bottom. Decision trees come in very handy for analyzing exploratory data since they are simple to analyze and comprehend. In our work, a DT classifier was fed the extracted characteristics from the CNN models to see how well it could discriminate between healthy and sick leaves.

IV. Experimental Setup

A. Environmental Setting

The investigation was carried out through experimentation on a ×64 processor, an Intel(R) Core i5 8265U CPU operating at 3.60GHz to 3.71GHz, equipped with 12 GB of DDR4 RAM, and running Windows 10. Applications for image processing were run on Google Colab. The exponent of our model was TensorFlow. For optimization, we used the Adam optimizer. Training the proposed model takes more than 4 hours, and testing takes around 1 hour.

B. Parameter Setting

The proposed model was trained using 20 epochs and a minimum batch size of 32 to detect the strawberry leaf scorch diseases. The recommended method's training size was 0.8, its validation size was 0.13, and the test size was 0.7. The values of all the parameters used during the training process are shown in Table II.

TABLE II
Experimental Parameters Valule

Parameters	Values
Batch Size	32
Image Size	224*224
Epochs	20
Classes	2
Fold	5

V. Result & Discussion

The outcome of the proposed strawberry leaf disease detection model was evaluated using multiple performance analysis metrics, including accuracy, precision, recall, and F1-score. To ascertain the most efficient method for identifying strawberry leaf diseases, we experimented with different configurations of feature extraction models VGG16, ResNet50, EfficientNetV2B0, and MobileNetV3. Also utilized three machine learning classifiers: Random Forest, Support Vector Machine, and Decision Tree. This section provides a thorough analysis of the experimental findings.

A. Result Analysis

In order to detect strawberry leaf disease, Table III compares the effectiveness of several deep learning models with a range of machine learning classifiers. The most effective model is ResNet50 with the SVM classifier, which achieved 99.80% accuracy on both the test and validation data across all evaluation metrics. This indicates that the model performed exceptionally well in categorizing healthy and infected leaves without making any error. Other models, such as EfficientNetV2B0 and VGG16, also showed excellent performance and high accuracy but were not as perfect as ResNet50 with SVM. Compared to the other models, MobileNetV3 typically performed worse, particularly with the Decision Tree classifier.

Figure 3 compares the validation accuracy achieved by three machine learning models—Support Vector Machine, Decision Tree, and Random Forest across four deep learning feature extraction methods: ResNet50, EfficientNetV2B0,

TABLE III
COMPARISON TABLE OF ALL MODELS AND CLASSIFIERS

Model Name	Classifier	Accuracy (%)		Precision (%)		Recall (%)		F1-Score (%)	
		Validation	Test	Validation	Test	Validation	Test	Validation	Test
ResNet50	**SVM**	**0.998**	**0.998**	**0.998**	**0.997**	**0.997**	**0.996**	**0.997**	**0.997**
	DT	0.965	0.992	0.964	0.992	0.965	0.992	0.96	0.991
	RF	0.996	0.993	0.994	0.993	0.993	0.995	0.994	0.995
EficientNetV2B0	SVM	0.955	0.975	0.955	0.973	0.957	0.973	0.954	0.977
	DT	0.833	0.914	0.835	0.917	0.838	0.913	0.835	0.913
	RF	0.942	0.954	0.944	0.953	0.943	0.942	0.946	0.953
MobileNetV3	SVM	0.964	0.953	0.965	0.955	0.967	0.945	0.968	0.953
	DT	0.773	0.714	0.773	0.716	0.775	0.715	0.778	0.714
	RF	0.924	0.893	0.925	0.897	0.927	0.897	0.927	0.896
VGG16	SVM	0.992	0.984	0.995	0.985	0.994	0.982	0.992	0.984
	DT	0.933	0.935	0.936	0.935	0.934	0.932	0.935	0.935
	RF	0.984	0.993	0.983	0.991	0.983	0.992	0.982	0.992

MobileNetV3, and VGG16. ResNet50 enabled SVM to reach the highest accuracy of 99.80%. Other models also perform well, but the Decision Tree classifier shows lower accuracy, especially when using MobileNetV3.

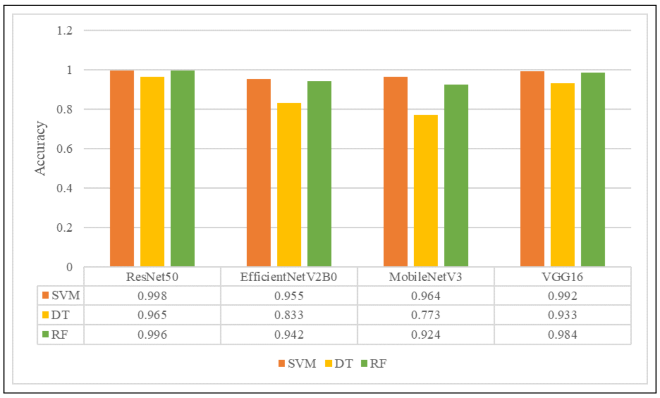

Fig. 3. Comparison of Validation Accuracy of all Models

Fig 4 compares the test accuracy of different models and classifiers. ResNet50 achieved the maximum accuracy of 99.80% while using SVM. Additionally, VGG16 performs remarkably well, especially when using SVM and RF. Accuracy is slightly lower with EfficientNetV2B0 and MobileNetV3, particularly when utilizing the Decision Tree classifier.

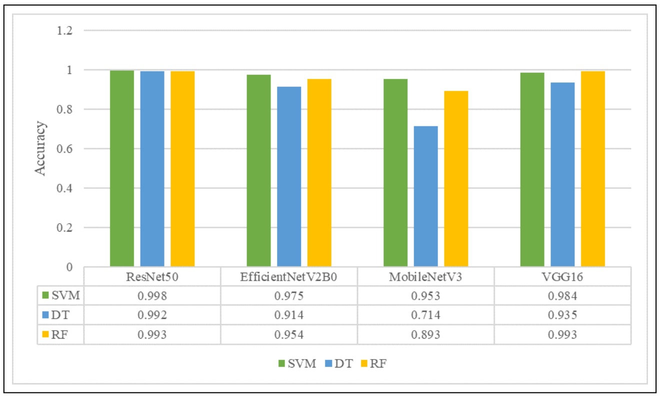

Fig. 4. Comparison of Test Accuracy of all Models

Fig 5 illustrates the confusion matrix for the ResNet50 model paired with the SVM classifier. The confusion matrix displays flawless classification results. With only one misclassification, it accurately detects 153 Healthy instances and 153 Leaf Scorch cases.

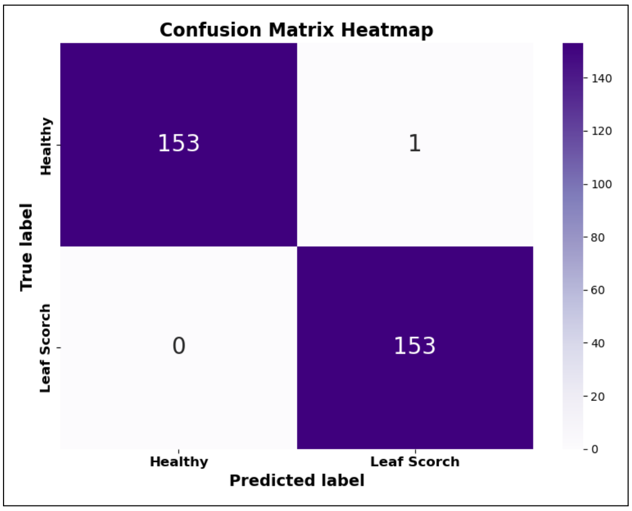

Fig. 5. Confusion Matrix for ResNet50 with SVM

Fig 6 presents the ROC curve for the ResNet50 model combined with the SVM classifier. The ROC curve shows excellent classification and an area under the curve (AUC) of 1.0; the model perfectly differentiates between the classes with no false positives or false negatives.

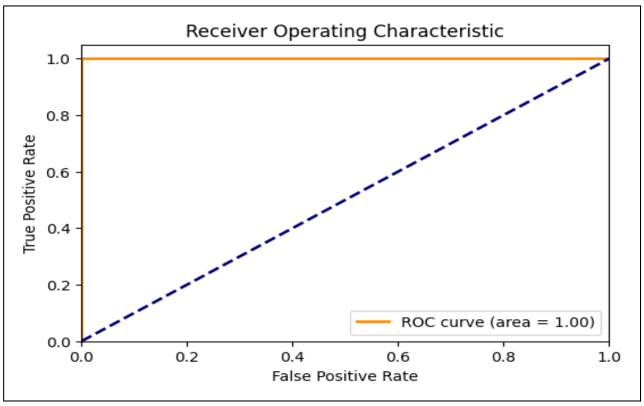

Fig. 6. ROC Curve for ResNet50 with SVM

B. Discussion & Limitation

The findings indicate that the model is successful and dependable at differentiating between healthy and infected strawberry leaves. The model's high validation and testing accuracy suggests that it can be used with confidence in real-world situations where accurate classification is essential. We also compared our model with several existing studies mentioned in the related work chapter, and the outcome of our model is better than any previous model we compared, shown in Table IV. Despite its strong performance, the proposed model has certain limitations. One key shortcoming is that it has been tested on a relatively limited dataset, which may affect its generalizability to diverse real-world scenarios. Additionally, our approach primarily relies on a feature extraction-based model, which, while effective, may not fully leverage the potential of end-to-end deep learning frameworks.

TABLE IV
COMPARISON WITH EXISTING WORK

Ref. No.	Model/Architecture	Highest Accuracy
[6]	VGG19, Inception V3, ResNet50, DenseNet121	94.40% (ResNet50)
[7]	Feature Fusion with Inception-ResNet, CCA - Canonical Correlation Analysis,	99.34% (CNN)
[8]	MobileNetV2-based StrawDet model	99.21% (Strawdet)
[9]	BerryNet-Lite, Efficient Channel Attention, and Multilayer Perception	99.45% (BerryNet)
[10]	SVM, KNN, RF, GoogleNet, Resnet and VGG	98.00% (CNN)
[11]	MobileNetV2, ResNet18, and EfficientNetB0,	99.00% (EfficientNetB0)
[12]	ResNet9-SE, (A modified ResNet model)	99.70% (ResNet9-SE)
Proposed Model	ResNet50, VGG16, MobileNetV3, EfficientNetV2B0 + SVM, DT, RF	**99.80% (ResNet50+SVM)**

VI. CONCLUSION & FUTURE WORK

Strawberry leaf disease detection and early-stage treatment are critical to disease prevention and improved strawberry production globally. One of world agriculture's most essential and challenging jobs is identifying and categorizing Plant leaf diseases, especially strawberry leaf diseases. This study uses machine learning and convolutional neural networks to build a hybrid machine-learning model that demonstrates the exciting potential to transform agriculture by accurately and effectively classifying diseases in strawberry leaves. The purpose of our suggested hybrid feature extraction based model is to increase the reliability and accuracy of strawberry leaf disease detection from image data. The proposed approach performs exceptionally well in the experimental findings, with the highest 99.80% testing and validation accuracy. This study establishes a baseline for further research and expands the diagnostic options for strawberry leaf diseases. In the future, we aim to develop an IoT-based strawberry leaf disease detection model and expand the dataset by incorporating more real-world images from different farms and countries to enhance performance. Additionally, We will develop a web application that allows users to identify strawberry leaf diseases by uploading photographs of the strawberry leaves to the website.

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