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MACHINE LEARNING AND DEEP LEARNING: A COMPARATIVE ANALYSIS FOR APPLE LEAF DISEASE DETECTION

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Abstract

Variations in the visual characteristics of leaf diameters allow for the differentiation of ill states, making leaves valuable indicators for the diagnosis of sickness. Accurate disease diagnosis depends on identifying the distinctive patterns that illnesses leave on foliage. Specialists or cultivators have frequently performed plant inspections, which may be costly and time-consuming. Automation of disease diagnosis is therefore crucial, particularly in areas with limited access to specialists. This work employs five classification algorithms Inception V3, Decision Tree, Support Vector Machine (SVM), and Random Forest to create a model for detecting diseases on apple leaves. The study's prime focus is Apple Rust, Apple Spot, and Apple Scab. To detect these illnesses, a relative examination of machine learning and deep learning models is carried out using the "Apple Leaves Disease Dataset."Among all the models tested, VGG19 achieved the highest test accuracy, reaching an impressive 95 percent.

Keywords: Classification, Deep Learning, Apple, Rust Leaf, Disease, Machine Learning, Scab, Spot.

I. Introduction

The worldwide economy depends heavily on agriculture, however, environmental protection is being neglected. Fog, hailstorms, and heavy rain can spread disease and harm crops [I]. Farmer suicide and agricultural losses are caused by plant diseases. The world economy and agriculture are harmed by these impacts. [XI]. Farmers identified medical conditions by hand. These techniques were too complex for small areas. Agronomy has changed because of technological advancements. The aforementioned advancements have made it possible to cultivate crops in challenging environments and automated several agricultural procedures. Farm productivity and income are increased by automation [XVII]. AI is required to detect illnesses in the leaves. With the use of modern technology, agricultural output might be increased by reducing losses and raising crop yields [XXIV]. DL(Deep learning) and ML(Machine learning) are used to identify illnesses in apple crops. China's fruit sector is plagued by scab and ring rot, two diseases of apple leaves caused by pests. [XIV]. Color, shape, and texture-based deep learning and data processing techniques enhance the ability to identify illness. These different qualities are combined by ANNs [VII], SVMs [XIII], and other techniques to automate the diagnosis of sickness. Tomato[IX], cucumber, cotton, grape, potato[XXII], and tomato[XXV] illnesses have all been treated using comparable techniques. Image processing and feature extraction techniques including fuzzy C-means, detection, and k-means clustering are used in disease diagnosis [XXVIII]. Farmers' decisions are aided by automated identification and detection of agricultural diseases. Apple planting and harvesting need to be improved. Because they boost planted area and yields, automated harvesting, and precision planting are in demand. Estimating yield, robot-assisted harvesting, and spraying are necessary for precision planting [III]. Apple picture segmentation is used in these techniques. Fruit leaf disease is difficult to diagnose due to the significance of CV indicators in agro-based and agricultural economies. Several fruit diseases can destroy crops. Apple leaf indicators may be used to diagnose other fruit plants [IV]. Several studies have examined the impact of rust, scab, and black spots on fruit yield and quality [V]. Therefore, there is a need for a quick-thinking automated system to identify and categorize ill apple leaves. Automatic detection of apple leaf disease has been accomplished by several researchers [VIII]. Current techniques for segmenting images of apple leaves differ. Color, spectral, and thermal cameras can identify airborne lasers (ALs) in orchards [XIX]. For the purpose of segmenting leaf pictures, color cameras offer geometric, textural, and color information. Threshold-based segmentation is used by analysts to exclude leaf pictures that exhibit significant color variations. Simple strategies are infamously effective. The various diseases, along with their symptoms, causes, and treatments, are shown in the table below.

Table 1:

Disease Name	Symptoms	Causes	Treatment
Apple Scab	The presence of dark, scaly lesions on the leaves is seen.	The subject of discussion is Venturia inaequalis, a type of fungus.	The utilization of fungicides and implementation of cultural practices
Apple Rust	The presence of yellow-orange dots on the leaves is seen.	Fungi (Multiple species)	The utilization of fungicides and the presence of alternate hosts.
Cedar Apple Rust	The presence of orange patches and lesions	Fungus belonging to the Gymnosporangium genus.	The application of fungicides for the purpose of eliminating junipers.
Fire Blight	The phenomenon is observed in plants where leaves exhibit wilting and blackening.	The microorganism under consideration is Erwinia amylovora, often known as bacteria.	The topics of interest for this discussion are pruning and antibiotics.
Powdery Mildew	The leaves appear to have a white, powdered covering on them.	Fungi belonging to the Podosphaera genus.	Two crucial aspects of agricultural operations are the use of fungicides and the establishment of suitable plant spacing.

The researchers preprocessed the dataset before using classification algorithms to pinpoint the locations affected by disease. The image given in Figure 1 depicts the entire strategy.

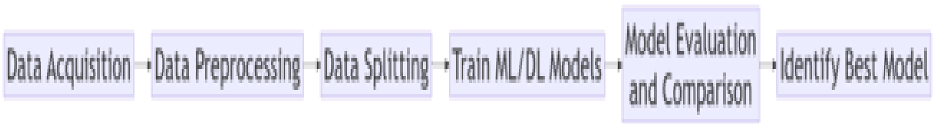

Fig. 1. Flow of Research

This study makes it easier to identify pertinent topics for more research and suggests possible ways that authors could develop the subject. To recapitulate, the following are the key goals of this project:

1. By merging ML and DL models, the working paper offers a novel method to boost the precision of apple leaf disease diagnosis.

2. Using the "Apple Leaves Disease Dataset (ALDD)" that was acquired from Kaggle, the research leverages a vast archive of 9,714 photos. This enables thorough evaluations of trained models in the field of AI.

3. The work offers a systematic description of the experimental approach, including data collection, preprocessing, and model training. The aforementioned transparency improves the repeatability of the study.

4. In addition to the disease classification, the study offers insightful practical consequences for causes, symptoms, and scientific language. The models' applicability to plant disease diagnosis is highlighted by the focus on attaining high accuracy for non-expert users.

The following is how the manuscript is organized: There is a thorough previous work described in Section 2. A detailed overview of ML models is given in Section 3. In-depth details on the datasets, pre-processing, and employed vectorization algorithms are provided in Section 4, which explores the study methodology. Section 5 described a detailed assessment of the distinctions between DL(deep learning) and ML(machine learning) models. As the study concludes, Section 6 summarizes the key ideas and offers suggestions for upcoming future research areas.

II. Related Work

The long-term survival of the apple business and efficient disease control rely on accurate diagnosis. We introduce a novel neural network architecture, Coordination Attention EfficientNet (CA-ENet), to advance the accuracy and proficiency of illness diagnosis. This architectural design helps to distinguish between several diseases that affect apples. Channel attention is used by the synchronized attention block in the EfficientNet-B4 network to find features geographically. Critical data such as channel and location are accessible to the model thanks to this integration. Depth-wise separable convolution is the method used by the convolution module to reduce parameters. The h-swish activation function is added to assess and expedite the process [XVI].A model was proposed that makes use of Actor's Spatial Pyramid Pool module and DeepLabV3+ semantic segmentation architecture. With this version, the accuracy of identifying faults in apple leaves was increased. Evaluation of the severity and identification of apple leaf disease progressed beyond semantic segmentation techniques such as PSPNet and GCNet. The presentation of the DeepLabV3+ model is further investigated in relation to optimizer selection, learning rate, and backbone network. As seen by the experimental findings, the model improved significantly, achieving 97.26% MPA and 83.85% MIoU[XIV].This study improves the YOLOv5s framework for apple leaf disease diagnosis. BiFPN features are integrated by the model prior to multidimensional integration. Convolutional block attention module (CBAM) and transformer are two attention methods that may reduce background noise and improve illness characterization. Accuracy and recollection improve over time. Experiments show that the 15.8-million-capacity BTC-YOLOv5s model can detect four apple leaf illnesses in the actual world. 84.3% of the model is mAP. The model can analyze 8.7 foliage photos per second using an octa-core CPU. The predicted model performs 12.74, 48.84%, 24.444%, and 4.2%

better than SSD, Faster R-CNN, YOLOv4-tiny, and YOLOx, respectively, in terms of mean Average Precision (mAP). Technology improves detection and processing. The model routinely obtains a mean average accuracy (mAP) of above 80%[XII] even in the presence of distorted photos, poor ambient light, and dark lighting.According to the article, apple tree leaf images may be classified into two groups using a CNN according to symptoms of disease. The CNN model consists of max-pooling layers, ReLU activation functions, and convolutional layers. The task under consideration is suited for binary categorization. With 91.11 percent accuracy on the dataset, the model performs admirably [XVIII].This study describes Apple-Net, a unique apple leaf disease detection technique. YOLOv5's architecture is enhanced with Apple-Net's Coordinate Attention and FEM features. To improve low-level feature mapping and semantic information extraction, YOLOv5 combines the feature pyramid and pan (path aggregation network) approaches. It is not possible to implement multiple-size data. To get over this limitation, FEM enhances multidimensional information retrieval. The use of cellular automaton (CA) significantly enhances detection. Empirical evidence shows that Apple-Net works better than four target detection methods. With an IoU of 0.5, Apple-Net has a mean average accuracy of 93.1% and precision of 95.9%. Apple-Net's capacity to identify apple leaf diseases is demonstrated by this study[XXVIII].A CNN with fewer layers was used in a study to get around computational limitations. The training dataset was increased using a variety of augmentation techniques without the addition of new images. There is usage of inversion, shift, shear, scaling, and magnification. This work used the publicly available PlantVillage dataset to train a CNN model. The data was chosen especially to aid in the identification of illnesses that affect apple orchards, with a focus on diseases that harm apple leaves, such as Scab, Black Rot, and Cedar Rust. Our comprehensive investigation shows that the predicted model can classify apple leaf diseases with 98% accuracy. Our model requires less storage and runs more quickly than other deep convolutional neural network (CNN) models[XXVII].YOLOX-ASSANano, a revolutionary deep learning framework fordiagnosis of apple leaf disease in real-time, is provided by the current research. With a number of changes, YOLOX-Nano's most recent version maximizes performance. The YOLOX-Nano backbone by-separate convolution (BSConv), an asymmetric ShuffleBlock, and a CSP-SA module improve feature extraction and object identification.We created the Multi-Scene Apple Leaf Disease Dataset to facilitate studies. The results of the experiments show that the YOLOX-ASSANano model with a parameter size of 0.83 MB has a mean Average Precision (mAP) of 91.08% on the MSALDD dataset and 58.85% on the publicly accessible PlantDoc dataset. Additionally, this model typically computes at 122 FPS. According to study, YOLOX-ASSANano can identify aample range of different plant diseases as well as apple leaf diseases in practical situations with speed and accuracy [XV].Deep learning is used to identify and classify apple leaf diseases. For this, CNN models function well. Convolutional neural networks (CNNs) favor the VGG16 design due to its simplicity and efficiency. This study uses VGG16 to classify illnesses in apple leaves.TensorFlow, Kaggle Notebook, and Keras are used by VGG16. Kaggle datasets related to apple leaf disease are apply to train and evaluate the model. The suggested approach optimizes apple leaf disease classification using sophisticated DL. The model's 93.3% validation accuracy for the dataset on apple leaf diseases [XXI] confirmed its efficacy. The novel apple leaf disease detection framework known as VMF-SSD (V-space-based Multi-scale Feature-fusion SSD) is described in this research. The primary objective is to maximize the effectiveness of disease detection at various sizes. By using multi-scale feature extraction and a V-space-oriented placement branch, VMF-SSD enhances texture representation. Feature channels are ranked using attention techniques in several aspects. On the test dataset [XXVI], VMF-SSD processes 27.53 frames per second with an average accuracy of 83.19 percent. This project aims to develop a model for detecting apple leaf diseases. Three feature extraction strategies are employed: Hu Moments, Haralick Texture, and Color Histogram. This study evaluates machine learning techniques for identifying and categorizing apple leaf diseases, including Black Rot, Cedar Apple Rust, and Apple Scab. The "Plant Village Dataset" [XX] is used in the analysis.

III. Methods

Supervised ML aims to determine the optimal hyperplane for the binary classification margin. In this procedure, SVMs are employed for both classification and regression. In Random Forest Classification, bootstrapping and random feature selection for each node create a "forest" of decision trees that reduce instability and overfitting. The technique uses a majority vote or mode to combine forecasts from each tree, which significantly improves accuracy and decreases error. It is necessary to tune hyperparameters such as split attribute counts, maximum tree depth, and n_estimators. Out-of-bag error estimates are useful for assessing how well the model performs when dealing with unknown data. Inner nodes in hierarchical decision trees represent feature-based judgment points, while leaf nodes represent final classifications. Pruning can be used to reduce overfitting. It means keeping the model's generalizability while eliminating superfluous branches. Classification problems may be addressed with multi-layer neural networks and other hierarchical DL methods. These networks forecast the formation of new instance classes and automatically detect complex patterns and features in data using backpropagation training and non-linear activation functions. VGG-19 is a potent CNN with 19 layers and primarily 3x3 convolutional filters. Its deep yet simple design makes it an excellent choice for photo classification. VGG-19 can capture complicated hierarchical patterns because of its max-pooling layers for class prediction and entirely connected architecture. Deep learning in image processing is where VGG-19 shines, despite its heavy demand on computer resources. With its accuracy, computational efficiency, and artistic design, Google's Inception V3 deep convolutional neural network is revolutionizing picture and object identification. To minimize processing and improve pattern recognition, it employs modules that mix 1x1, 3x3, and 5x5 convolutions with factorization. Stability and efficiency are increased when an auxiliary classifier is used to monitor and guide training. Rather than using fully connected layers, the last stage of the model employs global average pooling to lessen overfitting and enhance generalization. Because of its speed and accuracy, Inception V3 can be used in a wide range of computer vision applications.

The layered and fundamental architecture of VGG 19 and Inception-V3 is exhibited in figure 1,2,3,4.

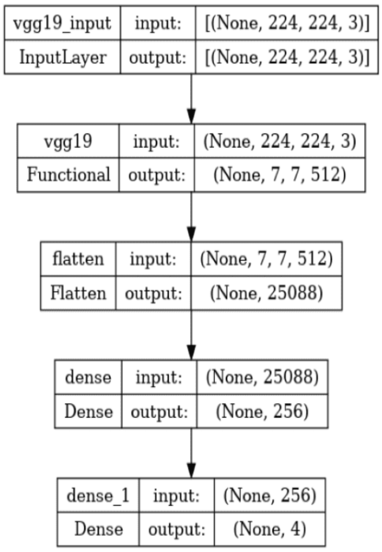

Fig. 2. Basic architecture of VGG 19 Models

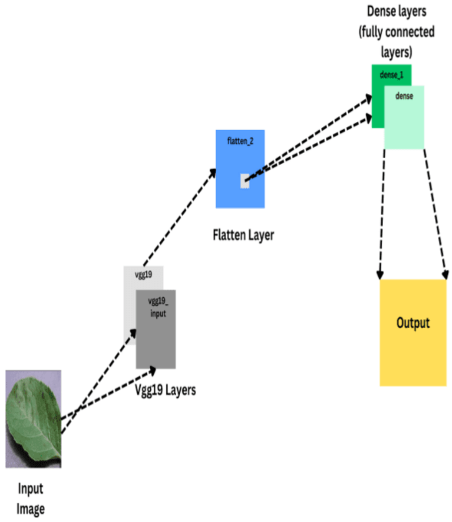

Fig. 3. Layered architecture of VGG 19 Models

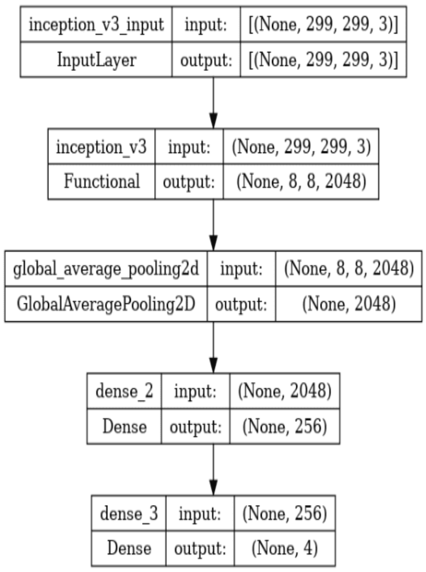

Fig. 4. Basic architecture of Inception V3 Model

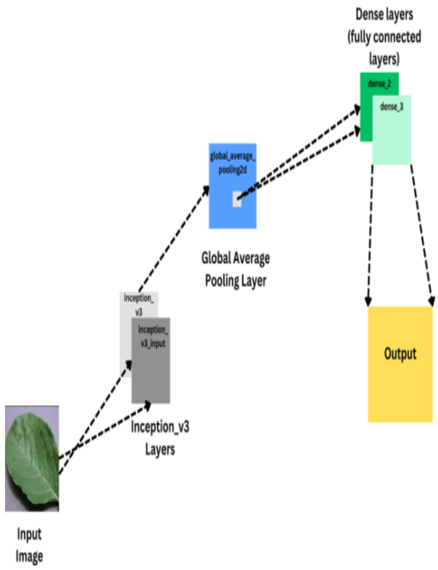

Fig. 5. Layered architecture of Inception V3 Model

III. Experiment Results

The specifics of the experiment, such as data collection, parameters, and outcomes, are covered in this section. Methods and data are used to explain each model's performance. Figure 1 illustrates how apple illnesses are recognized from leaf pictures using a ml & dl classification model. In order to categorize plant leaves as healthy or sick and to classify each sickness, experts first take images of the leaves and comment on them. It is possible to improve, resize, and filter the images. After that, the tagged samples are separated into training and test sets. To make predictions, we then employ sophisticated, previously taught ML-based models. By examining these forecasts, the system's accuracy is assessed. Non-specialists can identify and diagnose plant diseases with precision by following certain protocols.

Dataset

This study assessed the efficacy of multiple pre-trained ml & dl classification models in distinguishing between various plant leaf diseases using the publicly available "Apple Leaves Disease Dataset (ALDD)" from Kaggle. There are 9,714 photos in the dataset utilized for this study, which is called the Apple Disease Dataset. These photos have been divided into four distinct groups: spot, rust, lesion, and healthy. A partitioning technique is used to assign 80% of the entire picture dataset to the training set and reserve the remaining 20% for evaluating the model's performance. The following Fig. 2 provides a graphical representation of the dataset. Table 2 is used to give a detailed description of the dataset.

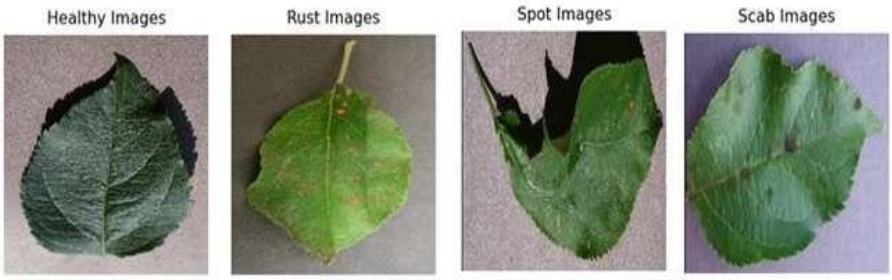

Fig. 6. Sample Apple leaf images

Table 2: Description of Apple Leaf Disease Dataset with symptoms

Disease Class Name	Dataset	Symptoms	Scientific Name	Caused due to
Healthy	2510	Green Leaves	-	-
Rust	2200	Rust color spots and Yellow leaves	Gymnosporangium juniper-Virginianae	Fungus
Scab	2520	Black dark lesions on the upper surface of leaves	Venturia	Fungal
Spot	2484	Irregular-shaped spots on the upper surface of leaves	Venturia inaequalis	Fungal Infection

Experimental Setup

On both datasets, the ALDD dataset was the subject of experiments involving the binary classification of positive or negative cases. About 80% of the photos were utilized for training, while 20% were used for testing. The experiment made use of an Intel(R) Core(TM) i5-3210M CPU running at 2.50GHz. The Kaggle platform was used for the study. The experiment relied heavily on important Python modules like Seaborn to improve plot aesthetics, matplotlib.pyplot to generate visualizations, and sklearn.metrics to evaluate classification metrics. The experiment's execution and subsequent analysis were accelerated thanks to the collaboration of these libraries. Table 3 and Figure 6 provide dataset characteristics, including the number of training and testing photographs, and classes overall.

Table 3: Distribution of Dataset

Sr No	Image Class Name	Total Images	Training Dataset	Testing Dataset
1	Healthy	2510	2008	502
2	Rust	2200	1760	440
3	Scab	2520	2016	504
4	Spot	2484	1987	497

The distribution of images is shown in the chart below, with rust representing 22.6%, scab representing 25.9%, spot representing 25.6, and healthy representing 25.8%.

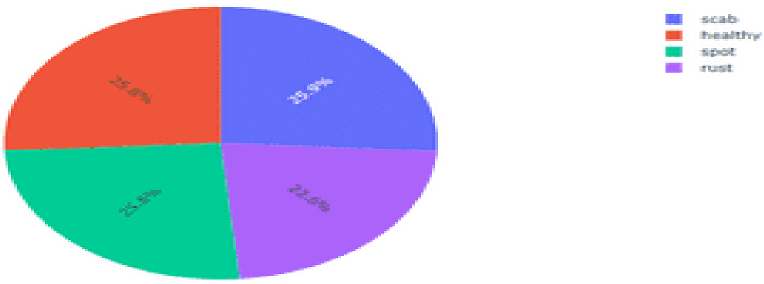

Fig. 7. Distribution ratio of Dataset

Evaluation Parameters

Accuracy, precision, recall, and F1-score were evaluated between the suggested model and other models.

Among all these parameters, accuracy is the most commonly used metric. (True positive + True negative)/(True positive + False positive + True negative + False negative) is the formula for accuracy. True Positive divided by True Positive equals precision.

The recall is estimated by dividing the real positive by the erroneous negative.

2x((Precision + Recall)/(Precision + Recall)) is the F1 score.

IV. Comparison of all preexisting models

Machine Learning Model Comparison

With an accuracy of 64.02 percent, the Support Vector Machine (SVM) model classified four classes. Performance varied by category: Class 0 predicts accurately thanks to its high precision, recall, and F1-score. Class 2 forecasts were cautious due to their high accuracy but low recall. Class 1 was better able to recall events than Class 2. Class 3 had excellent recall and precision. Albeit the model's exactness is fair, enhancements could increment execution, especially in lower accuracy or review classes. Figures 7 and 8 depict the confusion matrix and class performance, respectively. The Random Forest model was 80.85% accurate based on the case-to-occurrence ratio of the test dataset. Class 0 has an F1-score of 87 percent, 89% accuracy, and 85% recall. Class 1 had an F1-score of 82%, recall of 78%, and accuracy of 86%. Class 2 had a 74% F1-score, 77% recall, and 71% accuracy. Class 3 had an F1-score of 81%, 83% recall, and 80 percent accuracy. The macro averages for precision, recall, and F1-score in our Random Forest model were 81%, resulting in an average accuracy of 80.85%. The confusion matrix and performance assessment are depicted in Figures 9 and 10. The Decision Tree model outperformed random chance with a prediction accuracy of 55.74 percent on the test dataset. Class 0 had an F1-score of 61%, a recall of 63%, and an accuracy of 59%. Class 1 had a 57% F1-score, 58% recall, and 56 percent accuracy. Class 2 had an F1-score of 49%, a recall of 50%, and an accuracy of 49%. Class 3 had a 55% F1-score, 52% recall, and 59% accuracy. The F1-score, accuracy, and recall macro averages for the Decision Tree model were 56%. Figures 11 and 12 show the confusion matrix and performance assessment.

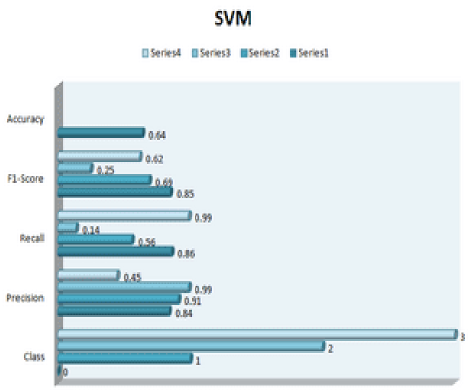

Fig. 8. Performance Evaluation of SVM

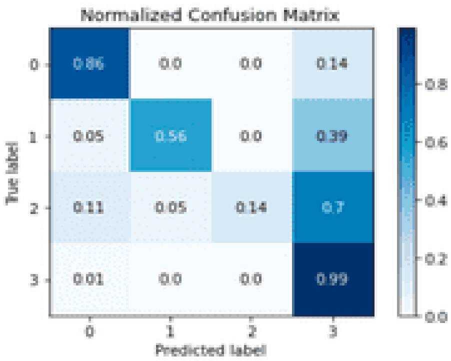

Fig. 9. Confusion Matrix of SVM

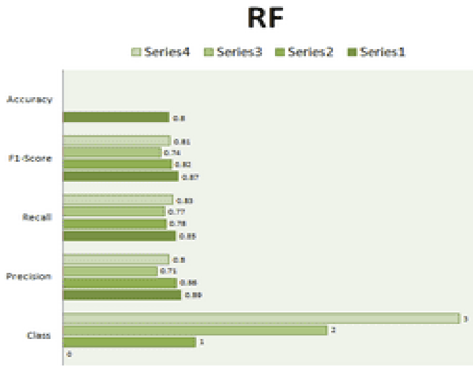

Fig. 9. Performance Evaluation of Random Forest

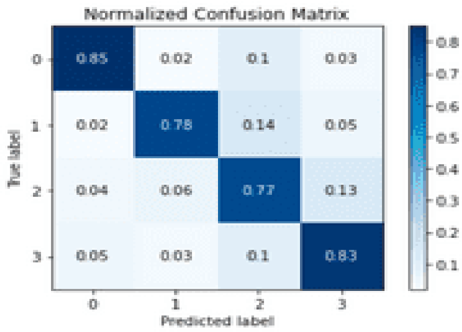

Fig. 10. Random Forest Confusion Matrix

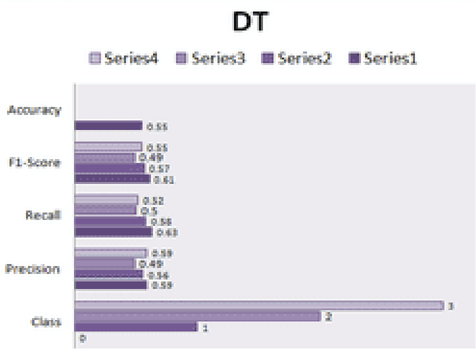

Fig. 11. Performance Evaluation of Decision Tree

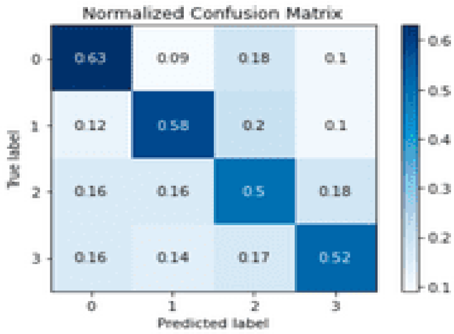

Fig. 12. Confusion Matrix of Decision Tree

Deep Learning Model Comparison

Over ten epochs, the VGG19 training log demonstrates consistent improvement, going from 0.6685 loss with 73.95 percent accuracy to 0.0459 loss with 98.41 percent accuracy. The model performs exceptionally well on the test dataset, with a 95.42 percent accuracy rate. Class 0 has a 90% F1-score, 93% recall, and 96% accuracy. Class 1's accuracy is 93%, recall is 99%, and F1-score is 96%. Class 2 has a 98% accuracy rate, 100% recall, and a 99% F1-score. Class 3's accuracy, recall, and F1-score are 96%, 94%, and 95%, respectively. The 96% weighted and macro averages demonstrate that students performed well across the board. Similar to the InceptionV3 model, the accuracy drops from 0.5875 to 0.0490 and from 81.76 percent to 98.43 percent. Overall accuracy on the test dataset is 92%. Class 0 has a 90% accuracy, 89% recall, and 90% F1-score. Class 1's recall is 89%, accuracy is 96%, and F1-score is 92%. Class 2's accuracy is 86%, recall is 97%, and F1-score is 91%. Class 3's accuracy is 95%, recall is 91%, and F1-score is 93%. Good performance is shown by the weighted and macro averages of 92%. Figures 13, 14, 15, 16, 17, 18, 19, and 20 show the outcomes.

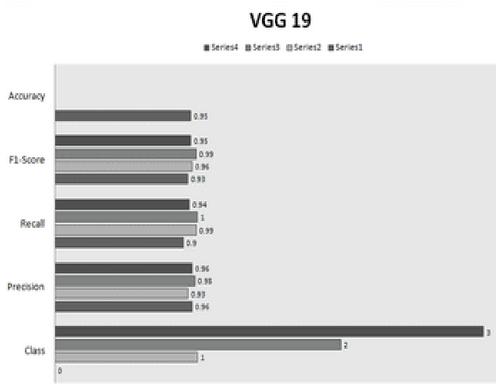

Fig. 13. Performance Evaluation of VGG 19 Algorithm

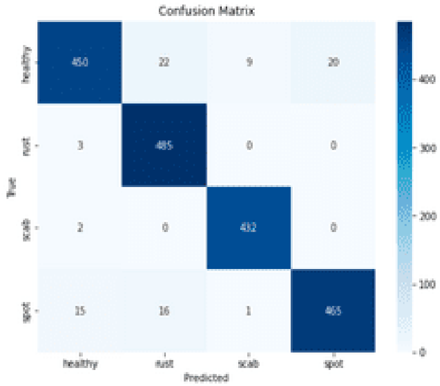

Fig. 14. Confusion Matrix of VGG 19

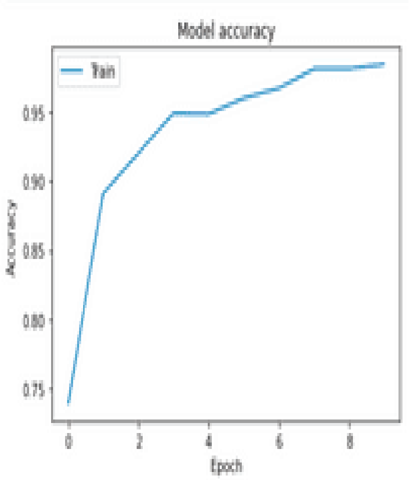

Fig. 15. Model Accuracy Growth Rate VGG-19

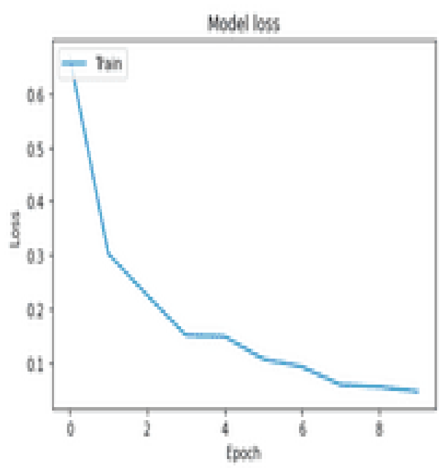

Fig. 16. Model Loss Growth Rate VGG 19

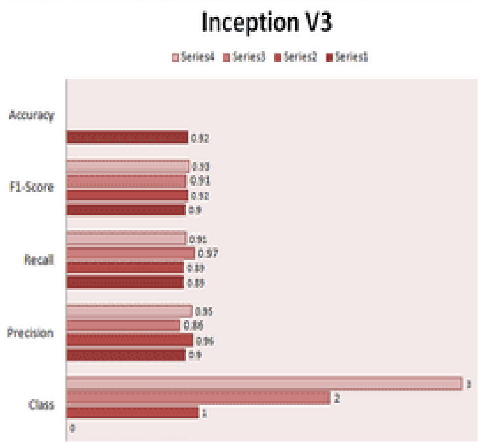

Fig. 17. Performance Evaluation of Inception V3 Algo

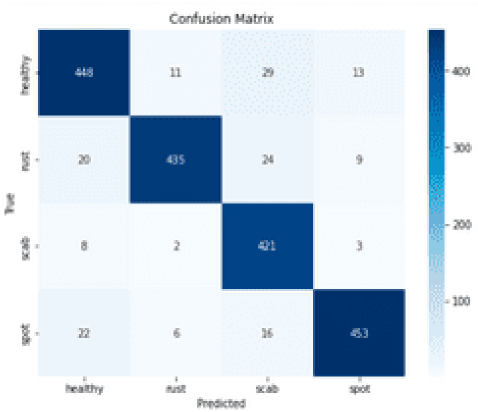

Fig. 18. Confusion Matrix of Inception V3

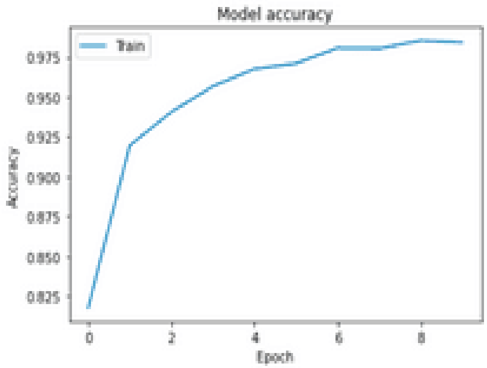

Fig. 19. Model Accuracy Growth Rate Inception V3

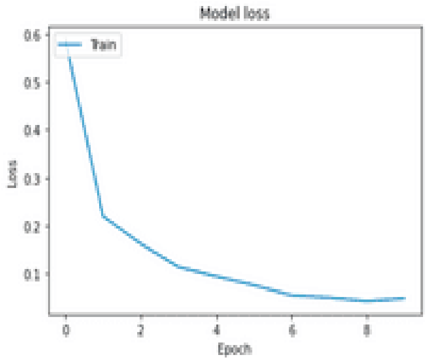

Fig. 20. Model Loss Growth Rate Inception V3

V. Result Comparison

Comparison of Pre-trained Proposed Model

The deep convolutional neural network (DGG19) and inceptionV3 models outperform SVM, RF, and DT on all metrics. InceptionV3 performs better than any other model on the task or dataset, with an F1-score of 0.96 and accuracy, precision, and recall of about 0.96. Furthermore, VGG19 has good performance, with all of its metrics around 0.93. Although it is lower than InceptionV3, it is still higher than the other models. In terms of accuracy (0.76), precision (0.81), recall (0.73), and F1-score (0.77), DT performs better than other well-known machine learning models. With an F1-score and recall value of 0.67, precision and precision values of 0.73, and accuracy values of 0.66, the Random Forest (RF) model performs better than the SVM model. The SVM model performs the poorest, with an accuracy of 0.75, a recall of 0.54, and an F1-score of 0.63. Figure 20 shows the comparison of all models with different parameters.

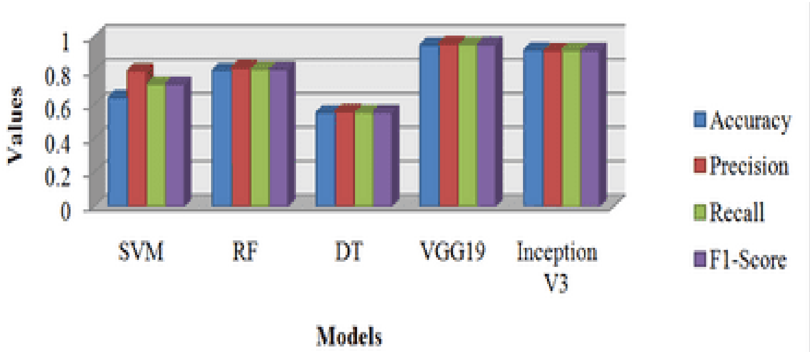

Fig. 21. Comparison of all models

Comparison with the existing model of the proposed model

The implications of our work and the comparison between the proposed models and existing research were outlined in the table below 4.

Table 4: Comparison of the existing model of the proposed model

Reference	Dataset	Algorithm	Class	Accuracy(%)
Bracino	Plant Village	SVM	Black Rot, Scab, Cedar Rust	85,64,81.70
Chandel	RGB	K-Means Custering	Powdery mildew	74.60
Jiang	ALDD	CNN	Spot	78.80
Zhong	ALIDD	Deep CNN	Multi	92.29
Our Model	ALDD	Deep Learning	Multi Class	95

VI. Conclusion

In conclusion, our research demonstrates how crucial it is to implement automated methods for diagnosing crop diseases, with an emphasis on apple foliage. Automated detection is essential for the implementation of cost-effective agricultural practices because the visual characteristics of leaves serve as discernible indicators for a variety of diseases. By using five different classification algorithms, including VGG19, the authors aimed to establish the most effective approach for recognizing three common apple leaf diseases. The "Apple Leaves Disease Dataset" evaluation emphasized VGG19's remarkable 95% test accuracy, which demonstrates its potential for accurate disease identification. The foundation for scalable agricultural tools that incorporate automated models to facilitate prompt disease intervention is laid by our discoveries in the future. To create sustainable global agricultural systems, this study supports current precision agriculture programs and promotes further research into the use of ML and DL in agricultural disease identification. Enhancing model robustness and developing user-friendly interfaces that are practical for manufacturers are two potential areas for future research.

Conflict of Interest:

This paper did not involve any relevant conflicts of interest.

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