Comparison of Machine Learning and Deep Learning Classification Models for Apple Leaf Disease Detection

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Abstract: Diameter variations in the leaf's visual characteristics enable the differentiation of diseased conditions; thus, leaves function as distinguishing indicators. To facilitate disease detection, the ability to identify the distinct patterns produced by these pathogens on the foliage is crucial. Historically, the physical examination of plants has been delegated to experts or cultivators. Nevertheless, this methodology may require a substantial financial investment in addition to a considerable labor force. Given the circumstances, it is critical to prioritize the implementation of automated techniques for detecting agricultural maladies, particularly in regions with limited access to specialists. By employing five distinct classification algorithms, this study aims to develop a model capable of discerning the presence of diseases on apple leaves. The following are the methodologies: Inception V3, Support Vector Machine (SVM), Random Forest, and Decision Tree. The approach currently under contemplation conducts a comparative analysis of machine learning and deep learning models in order to identify diseases that manifest in apple leaves. Apple Rust, Apple Scab, and Apple Spot are the particular products that are the focus of the attack. An examination is conducted on the "Apple Leaves Disease Dataset" with respect to apple leaves. When compared to all other fitted models, VGG19 has demonstrated the highest level of test accuracy ever established, at an impressive 95 percent.

Keyword: Apple leaves, Machine Learning, Deep Learning, Classification, Disease Detection, Apple Scab, Apple Spot, Apple Rust

1. Introduction:

The intensification of the universal economy is intricately interconnected with the agriculture sector, which is currently encountering difficulties as a result of environmental negligence. Crop devastation and the spread of diseases can be attributed to environmental uncertainties such as hailstorms, fog, and rapid rain [1]. Plant diseases have a significant role in the decline of crop health, resulting in negative outcomes such as financial hardship for farmers and, in extreme cases, occurrences of suicide. The aforementioned consequences have a deleterious impact on both the agriculture industry and the worldwide economy [2]. Historically, farmers mostly employed manual inspection methods for the goal of identifying diseases. These approaches were characterized by their labor-intensive nature and limited applicability to small-scale locations. In recent years, notable advancements in technology have led to a paradigm shift in the agricultural sector. The aforementioned improvements have effectively enabled the production of crops in adverse environmental circumstances and have additionally automated a multitude of agricultural procedures. The adoption of automation has demonstrated significant benefits, leading to a considerable improvement in agricultural output and concomitant increase in farmers' revenue. [3–5].

Artificial Intelligence (AI) has garnered recognition as a unruly force within the agricultural zone, possessing the capacity to address numerous existing challenges [6]. Artificial intelligence (AI) is of paramount importance in the timely detection of diseases, namely in the realm of identifying leaf diseases. The present technological innovation holds the capacity to considerably augment agricultural output through the amplification of crop yields and the mitigation of losses. Scholars have conducted investigations into various artificial intelligence methodologies, such as machine learning and deep learning, with the aim of detecting agricultural illnesses, particularly those that impact apple crops [7].

China, a prominent global fruit producer, encounters various obstacles such as the occurrence of apple leaf diseases caused by pests, as well as the presence of ring rot and scab under certain conditions [8]. The integration of color, shape, and texture cues through the utilization of deep learning and data processing techniques has contributed to significant progress in illness detection. Artificial Neural Networks (ANNs) [9], Support Vector Machines (SVMs) [10], and various other methodologies are employed to categorize these distinctive attributes and facilitate the automated detection of diseases. The utilization of comparable methodologies has been observed in the management of diseases that impact several crops, including potato [23], grape[11], cotton, tomato [12], and cucumber[13].

Several image processing and feature extraction techniques, including k-means clustering, fuzzy C-means, and detection methods have been utilized to facilitate illness identification [14–16]. The advancements in technology have facilitated the automated detection and identification of various crop diseases, providing farmers with the knowledge necessary to make well-informed decisions and take appropriate actions.

The planting and harvesting of apples necessitate a substantial degree of manual work. The demand for precision planting and mechanized harvesting technologies has become increasingly urgent due to the continual increase of planting areas and the rising yields [17]. The achievement of precision planting necessitates the utilization of many strategies, such as yield estimation, robot-assisted harvesting, and precise spraying [18]. The segmentation of apple pictures plays a crucial role among these procedures.

Detecting indicators of sick fruit leaves in the field of computer vision (CV) presents a significant issue, especially due to the crucial role they play in agriculture and agro-based economies. Numerous pathogenic conditions affecting fruits can have a generous collision on the overall well-being of crops as well as the quality of fruits obtained at harvest. The identification of visible signs on apple leaves provides useful insights for the detection of diseases in different categories of fruit plants [19]. The presence of these lesions plays a vital role in identifying and diagnosing apple illnesses [20]. Extensive research has been conducted to thoroughly detail the adverse impacts of diseases such as rust, scab, and black spot on the yield and quality of fruits [21]. Hence, it is crucial to prioritize the creation of an automated computerized system that can effectively identify and categorize contaminated apple leaves at an early stage. A multitude of scholars in the respective domain have developed diverse techniques for the automated identification of illnesses affecting apple leaves [22].

In latest existence, researchers have utilized a range of methodologies to do image segmentation on apple leaves (ALs). Analysts employ color, spectral, and thermal cameras to acquire photos of airborne lasers (ALs) within orchards and discern them from other elements present in these photographs [23]. According to [24],thermal and spectral cameras are capable of capturing data pertaining to heat and spectral properties. The utilization of color cameras, which offer geometric, textural, and color-based information, has been widely employed in the process of leaf image segmentation (IS). Certain analysts utilize segmentation algorithms based on thresholds to extract photos that exhibit significant differences in color compared to the color of leaves. These strategies are renowned for their straightforwardness and effectiveness.

The below table will illustrate the different disease with their symptoms, causes and treatment.

Disease Name	Symptoms	Causes	Treatment
Apple Scab	The presence of dark, scaly	The subject of	The utilization of

	lesions on the leaves is seen.	discussion is Venturia inaequalis, a type of fungus.	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 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 presence of a white powdery coating on the leaves is seen.	Fungi belonging to the Podosphaera genus.	The application of fungicides and the implementation of appropriate spacing between plants are two important factors in agricultural practices.

Table 1: Category of Diseases with Symptoms, Causes and Treatment

The investigators used models of classification to identify illness regions after doing preprocessing on the dataset. The whole approach is shown in the graphic presented below.

Figure 1: Flow of Research

This study facilitates the identification of relevant areas for future research and proposes potential ways for the writers to add to the topic. To recapitulate, the primary objectives of this undertaking are as follows:

1. The study article introduces an innovative method that combines machine learning and deep learning models to enhance the precision of apple leaf disease diagnosis.
2. By utilizing the "Apple Leaves Disease Dataset (ALDD)" obtained from Kaggle, the study makes use of an extensive collection of 9,714 images. This facilitates comprehensive assessments of trained models within the domains of deep learning and machine learning.
3. The experimental procedure is comprehensively described in the paper, including data acquisition, preprocessing, and model training. The aforementioned transparency enhances the investigation's capacity for replication.
4. The study provides valuable practical implications regarding causes, symptoms, and scientific terminology, in addition to the classification of diseases. The emphasis on achieving high accuracy for non-expert users underscores the practicality of the models in the context of plant disease detection.

The manuscript is structured in the following manner: Section 2 has an extensive literature review. Section 3 provides an in-depth explanation of Machine and Deep learning models. Section 4 delves into the study methodology, providing comprehensive information on datasets, pre-processing, and the used vectorization algorithms. Section 5 provides a comprehensive examination of the comparison between Machine Learning and Deep Learning Models. Section 6 serves as the last section of the report, providing a summary of the main points and suggesting potential areas for further research.

2. Literature Review

Accurately diagnosing diseases that impact apple leaves is essential for effectively managing illnesses and ensuring the continued and sustainable development of the apple industry. To improve the accuracy and efficiency of disease detection, we propose Coordination Attention EfficientNet (CA-ENet), a new neural network design. The purpose of this architectural style is to identify and differentiate a wide range of diseases that might potentially affect apple trees. The EfficientNet-B4 network incorporates a coordinate attention block that employs channel attention to provide spatial location information for features. By means of this integration, the model may effectively get pertinent data, such as geographical position and channel information. To reduce the number of parameters, the convolution module utilizes a depth-wise separable convolution. In addition, the h-swish activation function is included [25] to assess and accelerate the operation. The authors suggested a model that combines the DeepLabV3+ semantic segmentation architecture with the Actor's Spatial Pyramid Pool module (ASPP). The main objective of this update was to enhance the accuracy in differentiating features associated with lesions on apple leaves. Significant advancements were made in the diagnosis and assessment of the severity of illnesses impacting apple leaves, exceeding traditional semantic segmentation models like PSPNet and GCNet. In addition, the investigation comprehensively analyzed the influence of many aspects, such as optimizer selection, learning rate, and backbone network, on the performance of the DeepLabV3+ model. The experimental results showed significant improvement, with the model achieving a mean pixel accuracy (MPA) of 97.26% and a mean intersection over union (MIoU) of 83.85%[26].

This research presents an improved version of the YOLOv5s model specifically developed for the identification of illnesses on apple leaves. Prior to integrating characteristics across several dimensions, the model does BiFPN integration. By using attention methods such as the convolutional block attention module (CBAM) and transformer, we may effectively reduce background noise and improve the characterisation of ailments. Recall and precision subsequently increase. Experiments have shown that the BTC-YOLOv5s model, with a capacity of 15.8 million, is capable of accurately detecting four different apple leaf illnesses in real-world situations. The model has a mean average precision (mAP) of 84.3%. Equipped with an octa-core CPU, the model has the ability to analyze 8.7 foliage photos per second. The predicted model outperforms SSD, Faster R-CNN, YOLOv4-tiny, and YOLOx in terms of mean Average Precision (mAP) by 12.74%, 48.84%, 24.444%, and 4.2% respectively. Technology enhances the accuracy of detection and processing. The model exhibits robustness by regularly achieving a mean average accuracy (mAP) of over 80%, even in the face of difficult situations such as dim illumination, low ambient light, and distorted images[27].

The study article proposes the use of a Convolutional Neural Network (CNN) to categorize apple tree leaf pictures into two unique groups, depending on the presence or absence of disease signs. The CNN model consists of many components, including convolutional layers, activation functions for Rectified Linear Units (ReLUs), and max-pooling layers. The current job under examination may be characterized as a binary classification issue. The model demonstrates exceptional efficacy with a remarkable accuracy rate of 91.11 percent when applied to the specific dataset [28]. This paper presents Apple-Net, a pioneering approach for the detection of illnesses on apple leaves. The YOLOv5 architecture is enhanced by integrating Apple-Net's Feature Enhancement Module (FEM) and Coordinate Attention (CA). The YOLOv5 model improves the extraction of semantic information and the mapping of low-level features by integrating the feature pyramid and pan (path aggregation network) approaches effectively. Implementing data at many sizes is not feasible. FEM overcomes this constraint by improving the

retrieval of information across several dimensions. The use of Cellular Automaton (CA) has greatly improved detecting capabilities. Based on empirical evidence, Apple-Net has superior performance compared to four target detection methods. Apple-Net achieves a precision of 95.9% with an IoU of 0.5, and a mean average accuracy of 93.1%. The present study offers data that supports the efficacy of Apple-Net in identifying diseases on apple leaves[29]. In order to overcome the constraints imposed by computing limits, a research study used a convolutional neural network (CNN) with a decreased number of layers. In order to increase the size of the training dataset without acquiring more images, several augmentation approaches were used. The techniques include inversion, shift, shear, scaling, and magnification. The CNN model used in this inquiry was trained utilizing the publicly available PlantVillage dataset. The material was carefully chosen to aid in the identification of diseases that have a substantial impact on apple orchards, with a special focus on ailments that often damage apple leaves, such as Scab, Black Rot, and Cedar Rust.Our thorough assessment demonstrates that the predicted model is very effective in identifying diseases that affect apple leaves, as seen by its remarkable classification accuracy of 98%. Moreover, it is essential to highlight that our model demonstrates enhanced efficiency in terms of execution times and decreased storage demands in comparison to several recognized deep convolutional neural network (CNN) models[30].The present study introduces YOLOX-ASSANano, an innovative and effective deep learning framework specifically developed for the real-time identification of apple leaf diseases. The current version is a modified variation of YOLOX-Nano, including several changes to optimize its performance. The incorporation of blueprint-separate convolution (BSConv), an asymmetric ShuffleBlock, and a CSP-SA module greatly improves the ability to extract features and accurately recognize objects in the YOLOX-Nano backbone.To improve experimental research, we have collected a comprehensive collection of data called the Multi-Scene Apple Leaf Disease Dataset (MSALDD). The experimental results show that the YOLOX-ASSANano model achieves a mean Average Precision (mAP) of 91.08% on the MSALDD dataset and 58.85% on the publicly available PlantDoc dataset, with a parameter size of just 0.83 MB. In addition, this model routinely reaches a computational speed of 122 frames per second (FPS). The study highlights the efficacy of YOLOX-ASSANano as a rapid and efficient approach for diagnosing apple leaf diseases in real-world environments, as well as its applicability for detecting many other plant ailments [31].
Deep learning frameworks are used for the purpose of detecting and categorizing diseases that impact apple leaves. CNN models are quite effective for this purpose. The VGG16 architecture is highly esteemed in the domain of Convolutional Neural Networks (CNNs) due to its exceptional effectiveness and simplicity. This work uses the VGG16 gene to classify apple leaf diseases.VGG16 utilizes the Keras, TensorFlow, and Kaggle Notebook frameworks. The model is trained and evaluated using a Kaggle dataset that contains apple leaf diseases. The proposed approach utilizes advanced deep learning methods to optimize the classification of illnesses that impact apple leaves. The model's validation accuracy of 93.3% on the apple leaf diseases dataset proved its effectiveness [32]. This paper offers an elaborate elucidation of VMF-SSD (V-space-based Multi-scale Feature-fusion SSD), an innovative approach for identifying illnesses in apple leaves. The primary objective is to optimize the efficiency of disease detection in areas of diverse scales. The VMF-SSD technique utilizes a V-space-oriented location branch and multi-scale feature extraction to enhance the depiction of texture characteristics. Attention techniques are used across several dimensions to ascertain the relative importance of feature channels. The empirical results show that VMF-SSD achieves an average accuracy of 83.19 percent and processes 27.53 frames per second on the test dataset[33].The main goal of this project is to construct a model that can effectively detect the presence of illnesses on apple leaves. Feature extraction employs three distinct methodologies: The three used characteristics are Hu Moments, Haralick Texture, and Color Histogram. This study does a comparative analysis of several machine learning models to identify and categorize the diseases Black Rot, Cedar Apple Rust, and Apple Scab that affect apple leaves. The inquiry pertains to a distinct subgroup of the "Plant Village Dataset" [34].

3. Methods

3.1 ML classification model

Machine learning classification involves the creation of models and algorithms that can automatically categorize incoming data into predetermined groupings. Segmentation is a crucial process in machine learning that enables the identification and analysis of data links and patterns. Therefore, previously unnoticed and distinct occurrences may be precisely categorized. A classification task employs feature sets or properties [35]. The aim of the approach is to establish a correlation between these characteristics and a pre-determined set of categories or designations. Through the use of an annotated dataset including accurate class labels, the model may be trained to unveil the connections between the input variables and their corresponding classes. After undergoing training, the model may be used to forecast the category that each new, unknown data item falls into. Binary classification entails the segregation of data into two different categories, whereas multiclass classification addresses situations when there are more than two classes. These two categories of categorization tasks are often encountered in many fields. Machine learning classification may be used in several areas, including image recognition, medical diagnostics [36], text sentiment analysis, and email virus detection. Logistic regression, decision trees, support vector machines, k-nearest neighbors, and ensemble approaches such as Random Forests and Gradient Boosting are often used algorithms in machine learning for classification applications. The selection of an algorithm depends on the attributes of the data, the intricacy of the connections between features and classes, and the particular demands of the classification assignment. Accuracy, precision, recall, and F1 score[37] are often used measures to assess the effectiveness of a classification algorithm.

3.1.1 SVM

SVMs are used for classification and regression in supervised machine learning. The basic objective is to find a hyperplane that best classifies data. In binary classification, the SVM identifies the hyperplane that maximizes the margin between classes, which is the distance between the hyperplane and the nearest data points from each class. Lines along hyperplanes exist in two dimensions. As dimension expands, the object becomes a plane or hyperplane. In binary classification, the SVM chooses the optimum hyperplane to partition data into two groups. The margin is the distance between the hyperplane and the support vectors, the closest class data points[38]. SVM improves this margin to enhance model generalization to fresh, unseen data. Support vectors are the data items closest to the hyperplane and most significant in picking the suitable hyperplane. Variations in non-support vector placement do not influence hyperplane location. In order to tolerate non-linear decision boundaries, SVM enhances input feature dimension. This conversion is dubbed the "kernel trick." Linear, polynomial, and RBF/Gaussian kernels are prevalent. Support Vector Machines (SVM) balance a smooth decision boundary and exact training point categorization utilizing the C parameter. A low C value encourages a narrower margin, but it may misclassify training points. Increased C values seek a tighter margin to appropriately identify all training items. SVM permits real-world misclassifications when data separation is poor. The C parameter controls soft margin. SVM may categorize several classes one-versus-one or all-versus-one. Push for Vector machines help in bioinformatics, image and text classification. Their effectiveness comes from handling high-dimensional data and linear and non-linear decision limits. SVMs may not generalize well on large datasets[39].

A linear Support Vector Machine (SVM) equation may be denoted by a weight vector (w) and a bias term (b) that define a hyperplane. The decision function for an SVM used for binary classification is defined as follows:

f(z)=sign((∑i=1nwizi)+b)

Here:

The vector z denotes the input.

The number of features in the input vector is denoted by n.

The weight associated with wi

A is the term for prejudice.

The decision function can be expressed more succinctly in terms of vectors as follows: f(z)=sign(wØz+b). SVM seeks to optimize the margin between classes while decreasing classification error by finding the best w and b values. This is usually an optimization problem with linear equations or inequalities to solve. SVMs employ kernel tricks for non-linear decision boundaries. The kernelized decision function is:

$f(\mathbf{z})=\text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(\mathbf{z}_i,\mathbf{z})+b)$

α_i represents the Lagrange multipliers determined after optimization.

i-th training example class label is y_i.

The kernel function $K(z_i,z)$ computes the higher-dimensional inner product.

3.1.2 Random Forest Classification

The ensemble learning method Random Forest Classification addresses decision tree overfitting and instability. It handles different data kinds and produces reliable predictions, making it useful in many fields. Random Forest creates a categorizing "forest" of decision trees using ensemble learning. The algorithm's strength is aggregating these trees, each created from training data and randomized at each split. Intentional variety minimizes overfitting and improves models.

Random Forest tree training sets are randomized using bootstrapped sampling by choosing and replacing training data sections. This gives each tree a distinct data view. For each node, the approach randomly selects a subset of characteristics to get the optimal split. Strategic feature selection improves tree decorrelation and model generalization. Prediction relies on a majority vote or mode for each tree. Ensemble improves accuracy and reduces tree mistakes greatly. Optimization of Random Forest requires hyperparameter tuning. Controlling model complexity and overfitting involves careful modification of n_estimators, maximum tree depth, and split attribute counts. Out-of-bag samples—data points outside each tree's training groups—estimate generalization error. An out-of-bag error estimate reveals the model's unknown data performance. Random Forest assigns importance to features. To define their classifying roles, features are assessed on anticipated performance. Random Forest is difficult yet used in banking, healthcare, image recognition, and bioinformatics. Its resilience and data type diversity make it a popular real-world solution. Random Forest uses decision tree predictions[40]. The generic Random Forest categorization determination rule is:

$\hat{Y}=\text{Mode}(\{T_1(\mathbf{X}),T_2(\mathbf{X}),\ldots,T_n(\mathbf{X})\})$

Here:

$\hat{Y}$ is the predicted class.

$\{T_1(\mathbf{X}),T_2(\mathbf{X}),\ldots,T_n(\mathbf{X})\}$ represents the set of predictions from individual decision trees.

The mode function predicts the final class from the set's most common class. Decision trees of the Random Forest design are trained utilizing subsets of training data and random feature sets at each division. The overall decision rule is made from several decision trees, but the dividing criteria used during training determine each tree's decision rule. Common separating methods include entropy and Gini impurity.

3.1.3 Decision Tree Classification

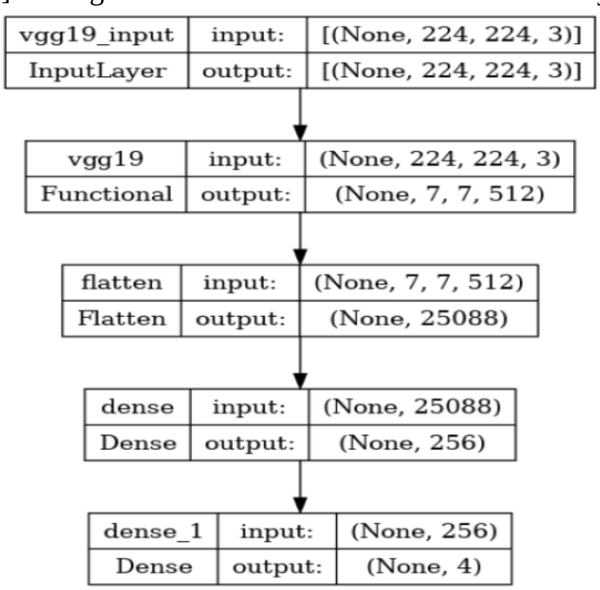
Machine learning makes decisions using decision trees. Conditions are generated from qualities. Top tree nodes represent the whole dataset. Internal tree nodes are decision points that divide the dataset by features. Branch terminations occur at internal or terminal leaf nodes, which evaluate circumstances. Mathematical internal node feature selection and thresholds govern decisions. Entropy and Gini impurity are used in classification issues to evaluate dataset disorder and the likelihood of misclassifying a randomly selected piece. Many regressions employ mean-squared error. Recursive decision tree construction splits the dataset until stopping requirements are fulfilled, such as a minimum number of samples in each leaf node or a preset depth. Interpretable and simple, decision trees are great for explanatory purposes, but they may overfit when big and incorporate data noise. To prevent overfitting, pre-pruning inhibits tree development; post-pruning eliminates branches. Pruned models generalize well on unobserved data. Decision trees simplify visual representation and decision rules for category and quantitative data. Parameter tweaking and trimming are critical since they are susceptible to overfitting and slight dataset variances. Ensembles like Random Forests use decision trees. Combining trees enhances model prediction accuracy and robustness[41]. Decision trees are essential to machine learning despite their disadvantages. Their uses include banking, healthcare, image recognition, and more.

3.2 DL classification model

Deep learning methods like multi-layer neural networks address classification problems. Large neural networks with layers develop hierarchical input representations in this context. These networks successfully predict new instance classes by automatically detecting complex data patterns and properties. With non-linearity, activation functions are keys to deep learning classification. Training uses backpropagation[42]. The model adjusts its parameters during training by comparing expected and actual results. Loss functions measure value differences, whereas stochastic gradient descent optimizes model parameters to remove them. Deep learning classification may improve medical diagnosis, natural language processing, and image identification. Handling different data formats requires convolutional and recurrent neural networks. Deep learning classification extracts complex attributes from raw data and delivers good predictions in many applications despite its high computing and data requirements.

3.2.1VGG 19

VGG-19, the Visual Geometry Group 19-layer model, is an advanced convolutional neural network. In image classification applications, it excels. The Oxford Visual Geometry Group's VGG-19 is noted for its simple, consistent design. Most of its 19 layers are 3x3 convolutional filters. The model's deep structure lets it reliably capture complicated hierarchical patterns in images, making it efficient for object recognition. The VGG-19 design has multiple convolutional layers followed by max-pooling layers. The feature hierarchy is rich and expressive with this design. The last layers provide class predictions with fully connected layers. VGG-19 is sophisticated yet simple and balanced, making it easy to understand and use. VGG-19 has been a key model for many computer vision applications; however it uses more computational power than recent designs. It advances deep learning in image processing significantly [43-44].The figure 2 and 3 will described the basic and layered architecture of model.



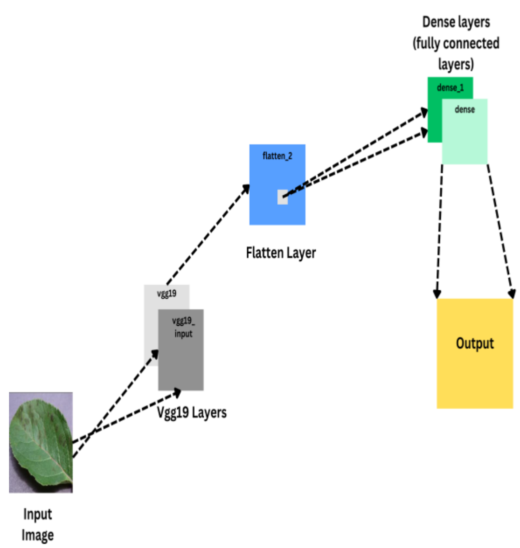


Figure 2: Basic architecture of VGG 19 Models Figure 2: Layered architecture of VGG 19 Models

3.2.2Inception V3

The Inception V3 deep convolutional neural network from Google revolutionizes picture and object identification. An advancement of Inception V1, Inception V3 mixes computational efficiency and accuracy with unique design. Inception V3's modules include max-pooling layers and 1x1, 3x3, and 5x5 convolutions. These modules help the network record properties at several spatial scales to analyze complex input visual patterns. Factorization methods partition bigger convolutions, a major achievement. Factorization reduces processing and improves visual pattern detection. Intermediate layer auxiliary classifier training distinguishes Inception V3. Auxiliary classifiers monitor and gradient the network, enhancing training stability and efficiency. Batch normalization speeds training and improves generalization by normalizing input across layer mini-batches. The last layer of Inception V3 uses global average pooling instead of completely linked layers. It reduces overfitting and condenses data to improve model generalization. Image classification benchmarks show Inception V3's versatility and ability to handle complex visual patterns. The architecture excels in transfer learning image categorization, object identification, segmentation, and feature extraction. The perfect mix between accuracy and processing efficiency makes Inception V3 suitable for real-world computer vision [45].The below figure 3 and 4 described the basic and layered architecture of model.

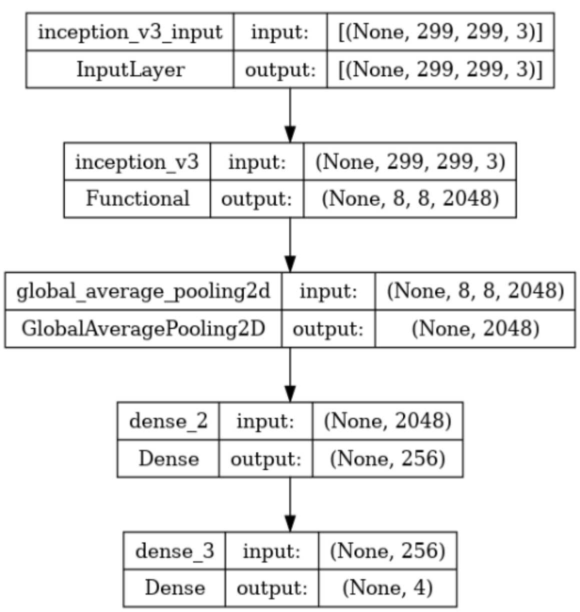


Figure 3: Basic architecture of Inception V3 Model

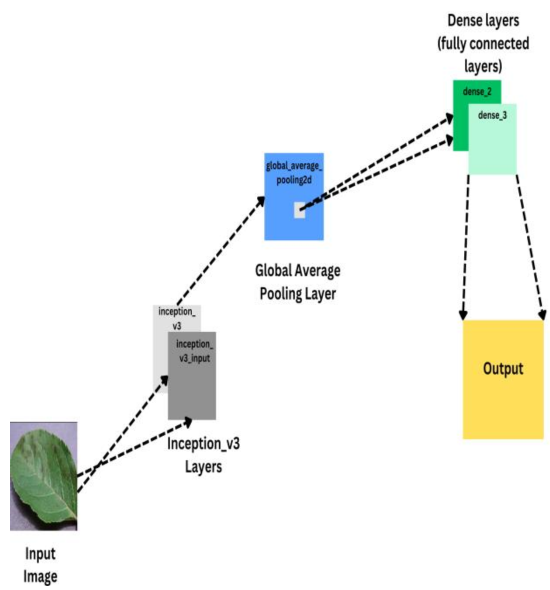


Figure 4: Layered architecture of Inception V3 Model

4. Experiment Result

This section delves into the specifics of the experiments, encompassing data collection, parameters, and the outcomes of the experimental procedures. The performance of each model is elucidated through a presentation of data and methodologies. This work employs a machine and deep learning classification model to identify and distinguish various apple illnesses based on leaf photographs, as seen in Figure 1. In the first stage, photographs of plant leaves are obtained and meticulously annotated by experts to classify them as either healthy or sick, with each specific ailment being assigned a unique label. The aforementioned photographs may undergo a range of preparatory treatments, such as filtering, resizing, and enhancement. Subsequently, the labeled samples are partitioned into two separate sets: a training set and a test set. Subsequently, we use intricately crafted pre-trained machine and deep learning models to accurately forecast outcomes. The results of these predictions are analyzed to assess the accuracy of the system. Within the field of plant disease detection and diagnosis, it is feasible to use methods that exhibit a notable degree of precision, enabling individuals without specialist knowledge to proficiently do these activities.

4.1 Dataset

This study used the publicly available "Apple Leaves Disease Dataset (ALDD)" from Kaggle to evaluate the effectiveness of several pre-trained machine learning and deep learning classification models in differentiating between different plant leaf diseases. The dataset used in this investigation, denoted as the Apple Disease Dataset, has a grand total of 9,714 photographs. These images have been categorized into four unique groups, namely healthy, rust, lesion, and spot. Figure 5 presents a graphical depiction of the samples derived from the four distinct categories of apple leaf. In order to streamline the process of training and evaluating the model, a partitioning scheme is used where 80% of the whole picture dataset is assigned to the training set, while the remaining 20% is designated for the purpose of assessing the model's performance.

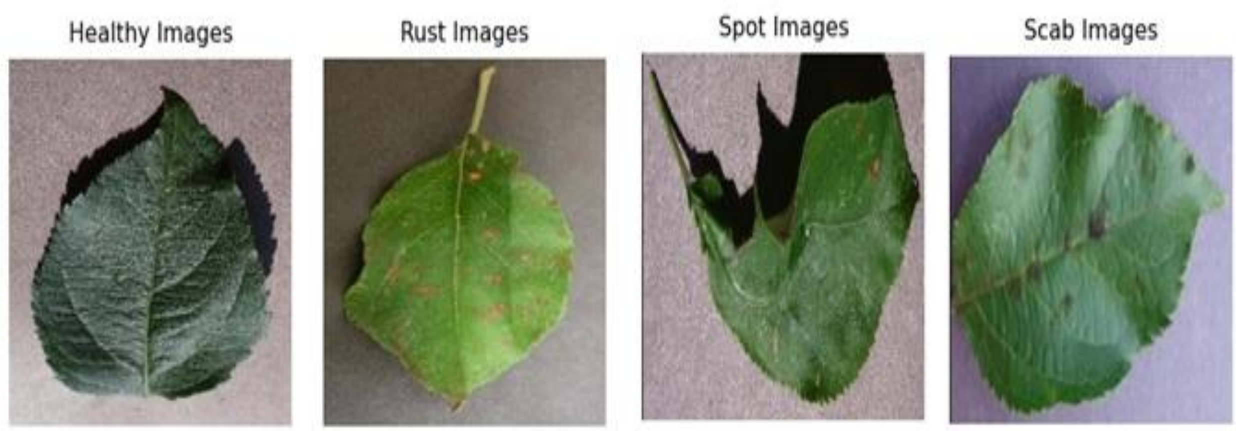


Figure 5:Sample Apple leaf images

Table2: 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 spot and Yellow leaves	Gymnosporangium juniper-Virginianae	Fungus
Scab	2520	Black dark lesions on upper surface of leaves	Venturia	Fungal
Spot	2484	Irregular shapred spots on upper surface of leaves	Venturia inaequalis	Fungal Infection

4.2 Experimental Setup

Experiments were executed on the ALDD dataset, involving the binary classification of positive or negative cases on both datasets. Eighty percent of the images were allocated for training, while the remaining 20% were designated for testing. The experimentation utilized an Intel(R) Core(TM) i5-3210M processor operating at a clock speed of 2.50GHz. The study was conducted on the Kaggle platform. Key Python modules, such as sklearn.metrics for evaluating classification metrics, matplotlib.pyplot for generating visualizations, and seaborn for enhancing plot aesthetics, were integral to the experiment. These libraries collaboratively facilitated the acceleration of the experiment's execution and the subsequent analysis. Additional details regarding the dataset are encapsulated in Table 3and figure 6, including information on the total classes in the dataset, the number of images per class, and the count of both training and testing images.

Table3: 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 are depicted by below chart such as rust with 22.6 percent,Scab 25.9 percent,spot 25.6 and healthy 25.8 percent.

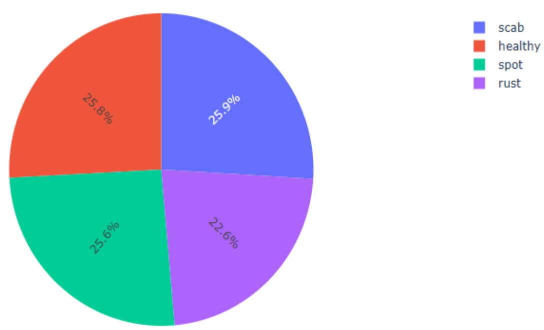


Figure 6: Distribution ratio of Dataset

4.3 Evaluation Metrics

The study compared the recommended model to others using accuracy, precision, recall, and F1 score.

The most frequent performance metric is accuracy.

Accuracy = ((True positive+True Negative))/((True Positive+False Positive+True Negative+False Negative)) (1)

It measures the model's ability to distinguish healthy and sick leaves Eq. (1).

Precision = True positive / (True positive + False Positive) (2)

Recall = (True positive)/((True positive+False Negative)) (3)

F1 score = 2x((Precision+Recall)/(Precision+Recall)) (4)

4.4 Comparison of all preexisting models

4.4.1 SVM

The Support Vector Machine (SVM) model achieved an overall accuracy of 64.02% in a classification job with four classes. Class-based evaluation demonstrates that performance exhibits variation across categories. Class 0 has outstanding precision, recall, and F1-score, indicating a high level of accuracy in predictions. Class 2 has remarkable accuracy; nonetheless, it struggles with recollection, suggesting an inclination towards making cautious forecasts. Class 1 has a greater ability to accurately collect all occurrences; however its ability to remember instances is lower. Class 3 attains an ideal balance between the ability to retrieve relevant information and the accuracy of the retrieved information. While the model's accuracy is reasonable, further enhancements have the potential to increase its performance, particularly in classes with lower precision or recall. Macro and weighted averages provide comprehensive metrics by considering the distribution of samples across all classes. The figure 7displays a comparison graph of distinct classes, including all parameters. Additionally, the figure 8 includes a confusion matrix.\

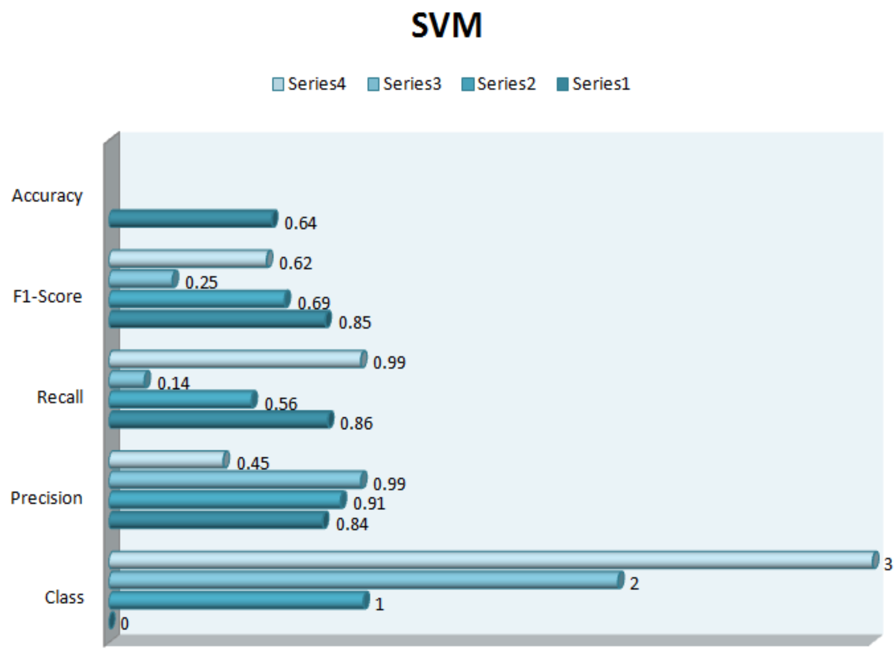


Figure 7: Performance Evaluation of SVM Algorithm

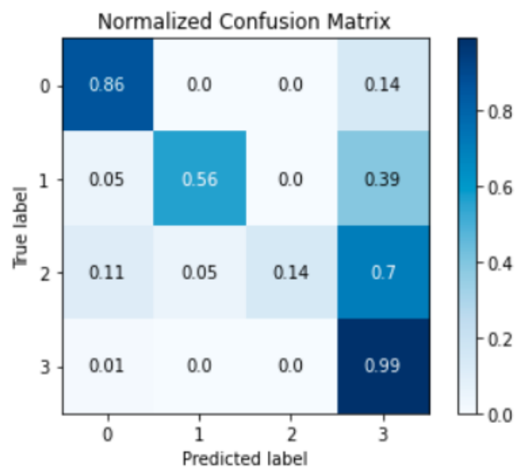


Figure 8: Confusion Matrix of SVM

4.4.2Random Forest

The Random Forest model attained a total accuracy of 80.85% when assessed on the test dataset. The accuracy metric quantifies the ratio of correctly identified cases to the overall number of occurrences in the dataset. The categorization report offers a comprehensive assessment of the model's performance for each specific class. The model's accuracy for Class 0, denoting the first category, is 89%. Consequently, the model accurately predicts this particular class with an 89% success rate. The recall of the model, which quantifies the accuracy of accurately identifying cases belonging to Class 0, is at 85%. Furthermore, the F1-score, a statistic that integrates accuracy and recall, stands at 87%. The figure 9 and 10 described the evaluation and confusion metrix.

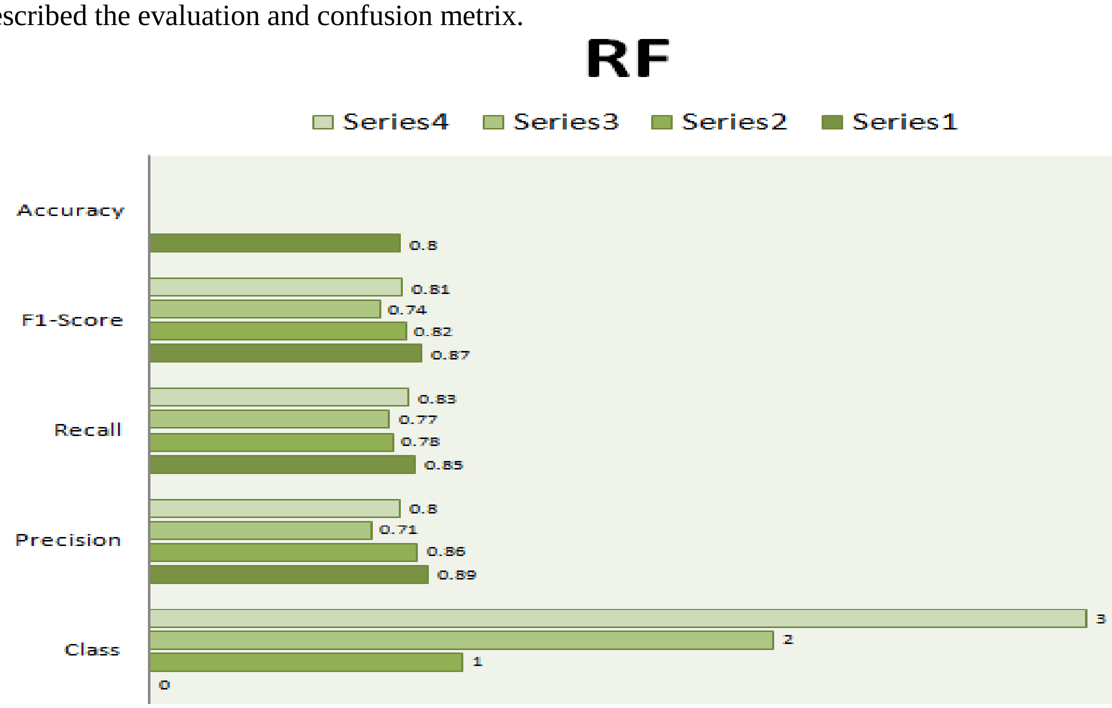


Figure 9: Performance Evaluation of Random Forest Algorithm

The prognostication of favorable results for Class 1 is 86% accurate, indicating a considerable level of precision. Nevertheless, with a recall rate of 78%, it is possible that the model may omit certain instances belonging to this particular class. The current F1-score is 82%.The precision of Class 2 is 71%, signifying that the model accurately forecasts this particular class with a 71% degree of accuracy. 77% is the recall rate, which measures the accuracy with which instances of Class 2 are detected; this corresponds to an F1-score of 74%.Class 3, denoting a high degree of accuracy in positive predictions, demonstrates a precision of 80%. Additionally, it exhibits an exceptional capacity to identify instances of Class 3 with a recall of 83%. In this category, the F1-score is 81%.The Random Forest model demonstrates a noteworthy performance, as evidenced by its accuracy rate of 80.85% on average. The mean performance across all classes is calculated using the macro average, which yields accuracy, recall, and F1-score values of approximately 81%.

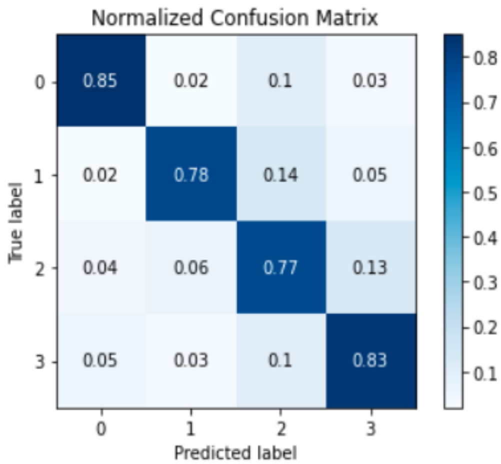


Figure 10: Random Forest Confusion Matrix

4.4.3 Decision Tree

The Decision Tree model achieves an accuracy of 55.74% on the test dataset. The accuracy statistic measures the ratio of successfully recognized instances to the total number of occurrences in the dataset. The categorization report offers a thorough evaluation of the model's performance for each specific class. The model has a high level of accuracy in predicting Class 0, with a frequency of 59%. The recall, representing the ratio of accurately predicted occurrences of Class 0 by the model, is at 63%, while the F1-score, a metric that combines accuracy and recall, is 61%. The accuracy of Class 1 is 56%, indicating a significant level of precision in optimistic predictions. The recall rate is at 58%, indicating a satisfactory capacity to detect occurrences of this category. The F1-score for this class is 57%. The accuracy of Class 2 is 49%, indicating that the model properly predicts this class with a precision of 49%. The recall, which measures the accuracy of identifying occurrences of Class 2, is at 50%, leading to an F1-score of 49%. The precision of positive predictions for Class 3 is 59%, demonstrating a substantial level of accuracy. The recall rate is at 52%, indicating a commendable ability to precisely detect occurrences of Class 3. The F1-score for this class is 55%. The Decision Tree model's total accuracy of 55.74% indicates that its predictions are somewhat superior to random chance. The macro average, which calculates the average performance across all classes, produces accuracy, recall, and F1-score values of around 56%. The figure 11 and 12 described the evaluation and confusion matrix.

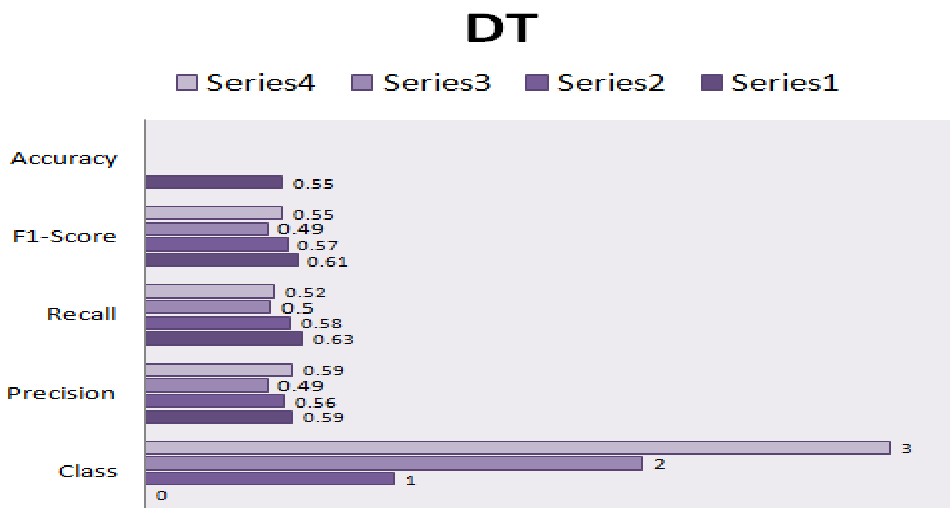


Figure 11: Performance Evaluation of Decision Tree Algorithm

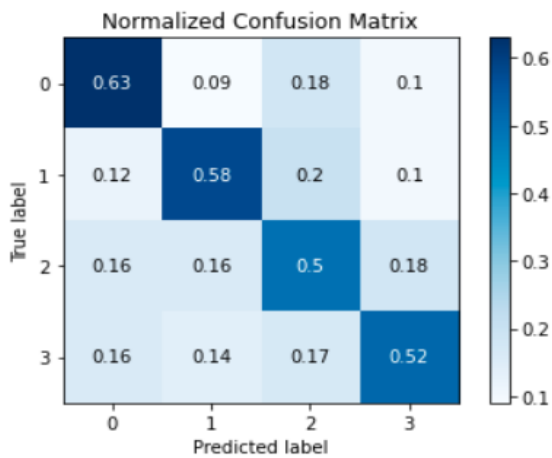


Figure 12: Confusion Matrix of Decision Tree

4.4.4Vgg19

The training log for the VGG19 model offers a comprehensive record of its learning progress across ten epochs, together with precise information about its performance on a test dataset. Throughout the instructional period, the model demonstrates a noticeable pattern of improvement. The procedure starts with the inaugural epoch, showcasing a loss of 0.6685, which is rather significant, and an accuracy of 73.95%. Following epochs demonstrate a steady decline in loss and an improvement in precision. By the tenth epoch, the model attains an impressive loss of 0.0459% and a training data accuracy of 98.41%. This indicates that the model has successfully acquired knowledge from the training dataset, as shown by its capacity to accurately identify complex patterns and provide predictions with a significant level of accuracy. The examination of the test dataset reveals that the VGG19 model exhibits exceptional effectiveness, achieving a complete accuracy rate of 95.42%. The categorization report offers a comprehensive assessment of the F1-score, accuracy, and recall for each class. The model has a 96% accuracy rate for Class 0, indicating that it accurately predicts this class 96% of the time. The recall, a statistic that quantifies the proportion of relevant examples correctly identified, has a value of 93%.

Additionally, the F1-score, a balanced metric that evaluates the accuracy of predicting instances belonging to Class 0, is 90%. Class 1 has a remarkable level of accuracy in its optimistic forecasts, with an excellent precision rate of 93%. A recall rate of 99% indicates an exceptional capacity to accurately recognize incidents that fall under this specific category. The F1-score for Class 1 is 96%. The precision rate of Class 2 is an impressive 98%, indicating a significant level of accuracy in its optimistic forecasts. A recall percentage of one hundred percent indicates that every relevant item was correctly categorized. A 99% F1-score indicates a significant level of accuracy, which includes both precision and recall. The Class 3 model has a recall rate of 94% and a precision rate of 96%, both of which signify a significant level of accuracy in generating positive predictions. The F1-score for Class 3 is 95%. The VGG19 model frequently exhibits its capacity to accurately recognize examples from all classes, as seen by its high values of overall accuracy, precision, recall, and F1-score. The macro average, which calculates the average performance across all divisions, yields metrics of about 96%, suggesting a well-balanced classification. Accounting for variations in class distribution, the weighted average yields comparable results. The below figure 13 and 14 illustrate the evaluation and confusion matrix of model.

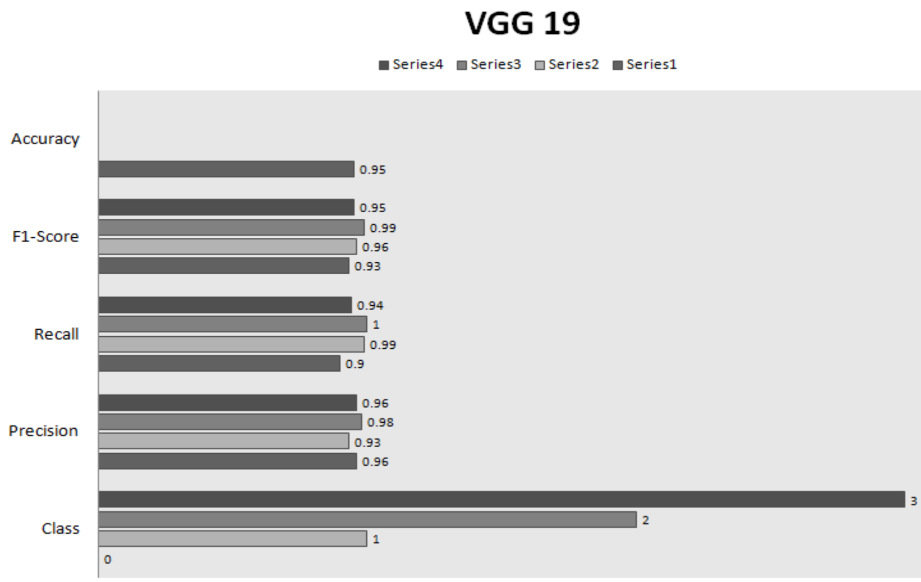


Figure 13: Performance Evaluation of VGG 19 Algorithms

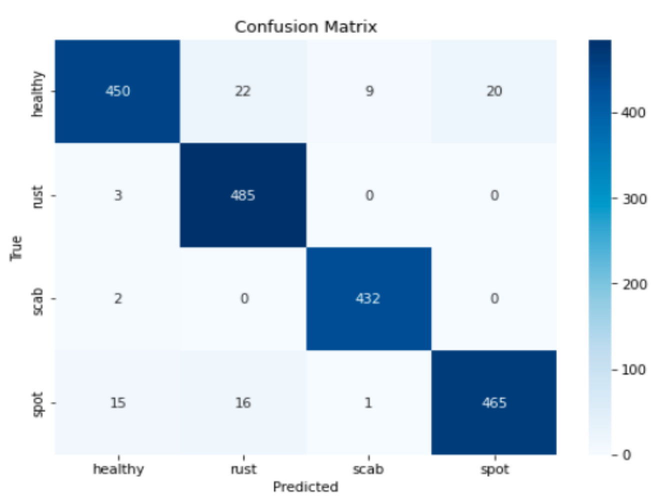


Figure 14: Confusion Matrix of VGG 19

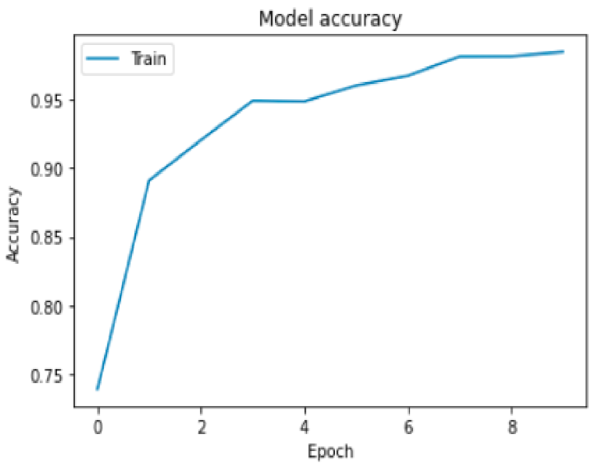


Figure 15: Model Accuracy Growth Rate VGG-19

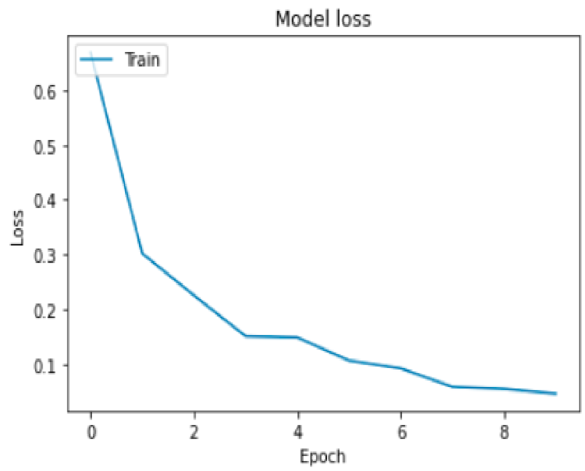


Figure 16: Model Loss Growth Rate VGG 19

4.4.5 Inception V3

The InceptionV3 model's performance shows a systematic progression across 10 epochs, as seen by its training log. The model starts with an initial decrease of 0.5875% in loss and achieves an accuracy of 81.76% in the first epoch. In the following epochs, the model undergoes significant improvement. During the tenth epoch, the loss on the training dataset reduces to 0.0490, while the accuracy climbs to 98.43%. This showcases the model's proficiency in acquiring knowledge effectively and its capacity to identify intricate patterns.Following evaluation on the test dataset, InceptionV3 demonstrates significant effectiveness, achieving an overall accuracy rate of 92%. The classification report provides a comprehensive analysis of the accuracy, recall, and F1-score for each class. The model achieves a precision rate of 90% for Class 0, indicating that it accurately predicts outcomes 90% of the time. The model has a high level of accuracy in predicting 89% of the actual cases belonging to Class 0. Additionally, the F1-score, which measures the model's precision and recall, is 90%. Recall is a quantitative measure that represents this fraction.Class 1 demonstrates a remarkable level of precision, reaching 96%, in its positive forecasts. With an 89% recall rate, the capacity to identify occurrences of this category is significant. The F1-score for Class 1 is 92%.The model attains a precision rate of 86% in Class 2, indicating a significant degree of accuracy in its optimistic forecasts. The F1-score is 91%, while the recall rate is 97%.The model achieves a precision of 95% for Class 3, indicating its capacity to make positive predictions reliably, and a recall of 91%. The F1-score for Class 3 is 93%.Overall, the F1-score, accuracy, precision, and recall metrics confirm that the InceptionV3 model is capable of accurately classifying cases across all classes with high precision and recall. The macro average, which considers the average performance across all classes, yields metrics of about 92%, indicating a well-balanced categorization. Even after adjusting for disparities in class representation, the weighted average produces similar outcomes. This demonstrates the InceptionV3 model's ability to effectively apply knowledge gained from training data to new, unseen examples, thereby proving its robustness and reliability in the assigned classification task.

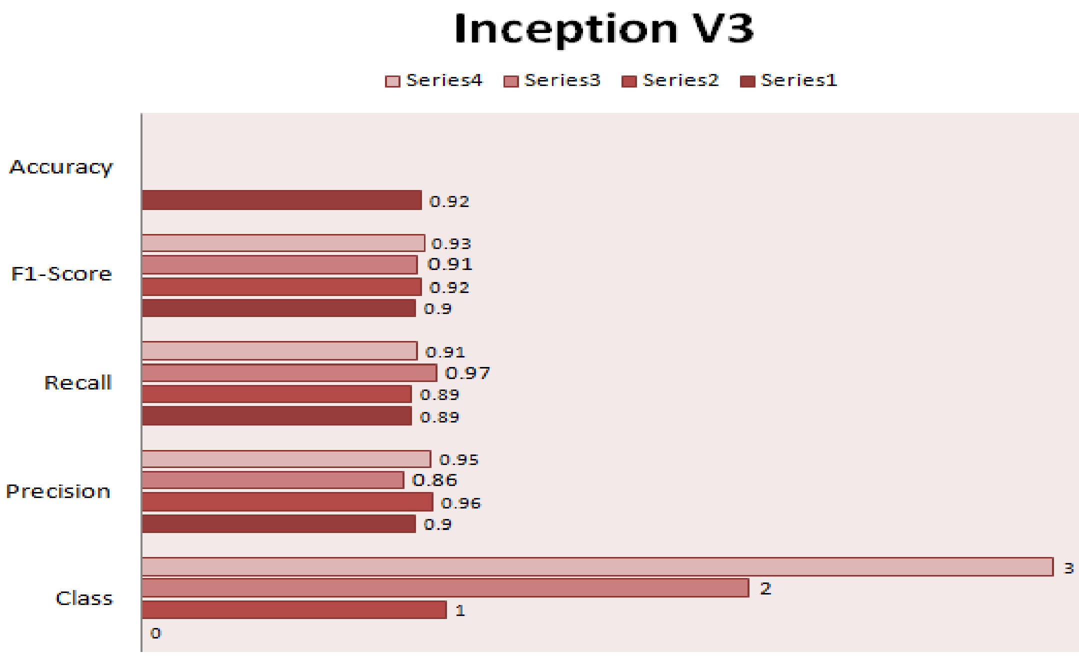


Figure 17: Performance Evaluation of Inception V3 Algorithms

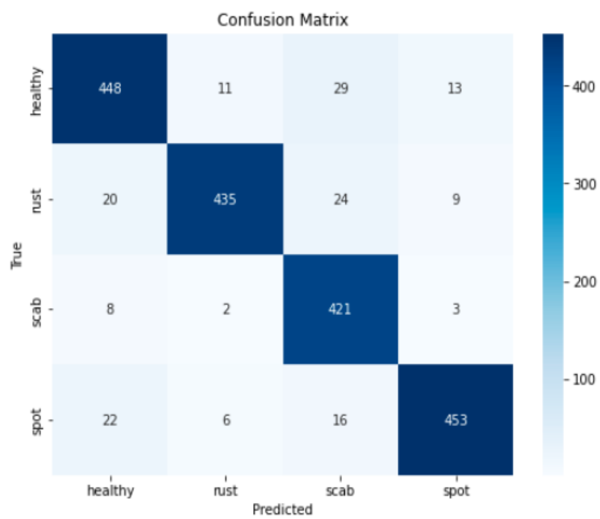
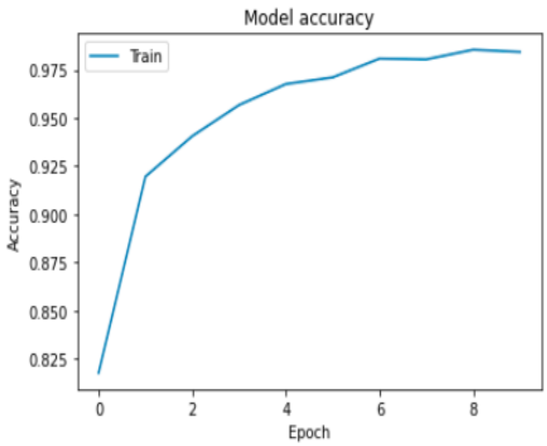


Figure 18: Confusion Matrix of Inception V3



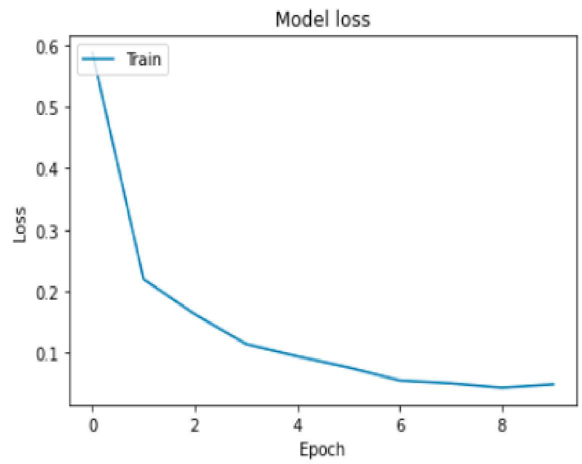


Figure 19: Model Accuracy Growth Rate Inception V3 Figure 20: Model Loss Growth Rate Inception V3

5. Result Comparison

5.1 Comparison of Pre-trained Proposed model

The deep convolutional neural network (DGG19) and inceptionV3 models outperform SVM, RF, and DT on all measures. InceptionV3 outperforms all other models on the task or dataset with an F1-score of 0.96 and accuracy, precision, and recall around 0.96. VGG19 also performs well, with all of its measures around 0.93. It is lower than InceptionV3, but still higher than the other models. Decision Tree (DT) outperforms other common machine learning models in accuracy (0.76), precision (0.81), recall (0.73), and F1-score (0.77). The Random Forest (RF) model outperforms the Support Vector Machine (SVM) model with F1-score and recall values of 0.67, precision and precision values of 0.73, and accuracy values of 0.66. The SVM model performs worst with an accuracy of 0.75, recall of 0.54, and F1-score of 0.63.The figure 20 illustrate the comparison of all models with different parameters.

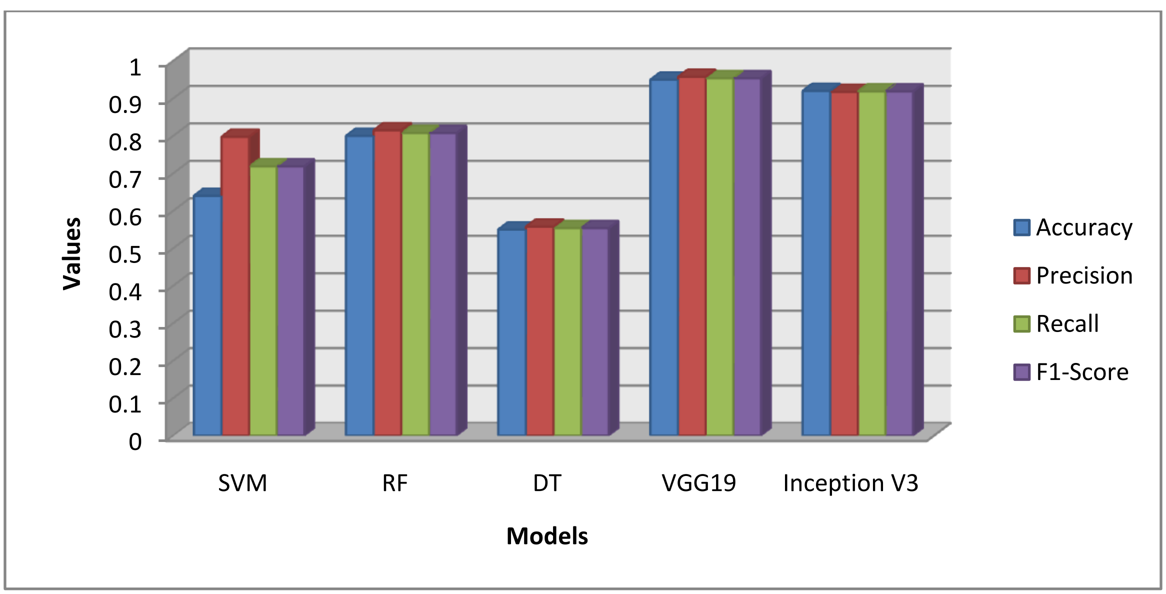


Figure 20: Comparison of all models

5.2 Comparsion with existing model of proposed model

The below table described the comparison of proposed models with existig study and descibed the imporatnt of our work.

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

Conclusion

In summary, our study underscores the critical importance of implementing automated systems for diagnosing crop diseases, with a specific emphasis on apple foliage. Because the visual attributes of leaves function as discernible indicators for a multitude of maladies, automated detection is indispensable for the implementation of economical agricultural methodologies. By employing five distinct classification algorithms, one of which was VGG19, our objective was to determine which method was most efficient in identifying three commonly occurring apple leaf diseases. The evaluation of the "Apple Leaves Disease Dataset" emphasized the remarkable test accuracy of 95% achieved by VGG19, which underscores its potential for accurate disease identification. In the future, our discoveries lay the foundation for scalable agricultural tools that incorporate automated models to facilitate timely disease intervention. Consistent with the objective of establishing sustainable global agricultural systems, this study encourages additional research into the utilize of machine learning and deep learning in agricultural disease detection and contributes to ongoing precision agriculture initiatives. Potential areas for future research embrace the improvement of model robustness and the creation of user-friendly interfaces that are feasible for producers to implement in practice.

Author Contibution

Anupam Bonkra contributed the statistics and tables to the manuscript and assumed the primary responsibility for composing the initial draft. Editing was conducted and data sources were managed by Sunil Pathak. Amandeep Kaur oversaw the entire procedure and guaranteed the work's precision and validity.

Conflict of interest

The authors declared no conflict of interest.

Funding information

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Data availability

Not applicable.

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