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Research Article

Apple Leaf Disease Identification: A Hybrid Multi-Scale Deep Learning Model

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ABSTRACT

Agricultural diseases have an impact on agricultural production and provide the agricultural sector with a number of significant problems. If any prior knowledge about the diseases and environmental conditions is anticipated, these difficulties can be overcome. Artificial Intelligence and computer vision-based methods are being used to this end in order to enhance the food chain. This study thoroughly examines customized models of deep learning for automating the diagnosis of apple leaf diseases. We evaluated SOTA CNN architectures, including our proprietary CNN, ResNet50, EfficientNetB3, and hybrid models, using the Apple Leaf Disease Dataset. Every model demonstrated remarkable performance, with validation accuracies surpassing 96%. Whereas the custom EfficientNetB3 model attained 100% accuracy, the custom ResNet50 model only managed 99%. These results entail that deep learning could be able to identify cedar apple rust, fire blight, apple scab, and powdery mildew on apple leaves. We assessed the models' disease classification recital using measures including recall, accuracy, and F1-score. This Study results reveal that the models performed exceptionally well on all criteria, indicating that they could correctly identify apple leaves that were healthy or ill. To sum up, our research improves automated agricultural disease detection systems and gives farmers powerful tools to lessen the burden of disease in apple orchards. By facilitating early disease identification and proactive control, the incorporation of deep learning algorithms into agricultural methods has the potential to guarantee sustainable production of apples.

Keywords: Deep Learning, CNN, Agriculture, Apple leaves, Disease, Hybrid Model, Resnet 50, Efficient net B3, Computer Vision.

INTRODUCTION

A combination of rain, fog, hail, or other weather-related phenomena can seriously impair the agriculture sector, which is vital to the world economy. A number of unidentified variables may have a negative impact on agriculture and facilitate the spread of illness. Plant diseases can lead to farmers experiencing psychological distress, financial difficulties, and even self-harm. The economy is significantly impacted by trivial rural practices [1]. Visual and physical examinations were the mainstay of medical diagnosis in the past, but they were time-consuming and had limitations. But technological progress, especially in automation, has changed agriculture. Research suggests that modern agricultural technologies can increase the income and output of growers. Artificial Intelligence is used by the agriculture sector to solve various problems. Apple leaf diseases can be detected by autonomous devices through the relevance of deep learning, image processing, and machine learning procedures for early leaf disease identification. If these technologies are successfully implemented, fruit production might rise and farmers' losses could be minimized. Vectors with form, texture, and color features have been the subject of extensive investigation. SVMs and ANNs are two popular classification techniques [2].China continues to be the world's top apple grower despite worries about apple leaf diseases. To identify agricultural diseases, universities are using machine learning and image processing. Different techniques are used to find anomalies. The synthesis of shape, texture, and color feature vectors is made easier by newly developed deep learning and data assessment algorithms, which facilitate the creation of feature vectors. Diseases are categorized in multiple ways [3], and SVMs and ANNs are two examples of models. Product developers can benefit from the fact that farmers can automate disease identification using a variety of feature segmentation techniques, including Roberts, Prewitt, Sobel, and fuzzy C-means detection. Diseases can affect the flora and reduce the quantity and quality of pears produced. Defoliation, a decrease in fruit quality and quantity, discolored leaves, and plant mortality are all possible outcomes of these infections

[4]. Apple leaves may be affected by diseases such as black rot, scab, powdery mildew, and fire blight. Olive-green patches on brown or yellow leaves are indicative of apple scab, a fungal disease caused by Venturia inaequalis. Because of the severe side effects and early leaf death caused by this disease, the fruit may be smaller and of lower quality. Concerning is also the cedar apple rust fungus, which results in yellow speckles on the undersides of leaves that turn orange-brown and are spotted with lesions. Podosphaeraleucotricha-affected apple leaves have a powdery, white granular mildew. Apple trees are badly damaged by Erwinia amylovora's fire blight. To maintain apple output, apple leaf diseases must be promptly diagnosed and treated. Conventional techniques for diagnosing diseases, like visually examining leaves, are laborious and unreliable [6]. The different varieties of apple leaves afflicted by different diseases are shown in Figure 1.

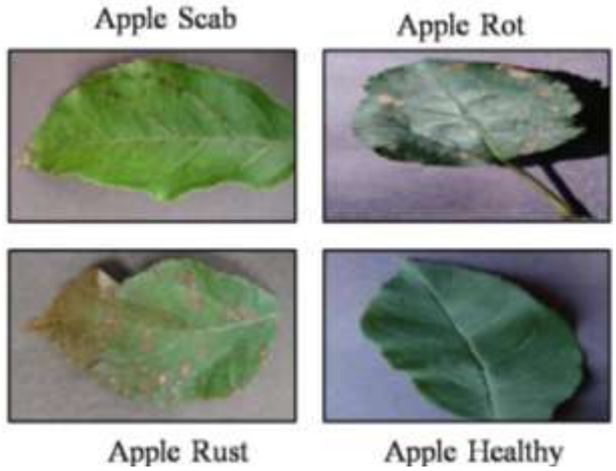


Figure1: Apple Leaves Types

The error rates of these approaches are substantial. The automation of agricultural disease diagnosis and control is improved by this work. There is a lot of potential in using computer vision to detect apple leaf disease. The previously mentioned techniques make use of statistical or deep learning algorithms to examine plant photos, spot leaf damage, and collect more information. A large body of research indicates that apple leaf diseases can be quickly identified by computer vision-based systems. Research shows that digital photos of leaves can be used to identify powdery mildew using CNNs. Table 1 provides a schematic illustration of apple leaf diseases.

Table 1: Apple Leaf Disease Taxonomy

Disease	Cause	Signs	Solutions
Apple Scab [7]	Venturia inaequalis	Small brown markings on fruit and branches; pale brown or olive-green streaks on the tips of leaves	- Removing impacted branches and applying fungicide
Cedar Apple Rust [8]	Gymnosporangium spp.	dots that resemble yellowish-orange cups	- Eliminating disease-causing Branches: Ending the Cycle of Disease
Powdery Mildew [9]	Podosphaeraleucotricha	Fruit, branches, and leaves have a white, powdered coating.	- Applying fungicide is an effective way to control orchards.
Fire Blight [10]	Erwinia amylovora	Entire plant wilting, darkening, or burned look	- Taking off diseased branches and giving antibacterial drugs

1.1 Objectives

- To create and put into practice a hybrid model for apple leaf disease detection that combines convolutional autoencoders (CAE) and convolutional neural networks (CNNs).
- To compare this hybrid model against the current state-of-the-art CNN models, ResNet-50 and EfficientNet B3, based on accuracy, precision, recall, and F1-score.
- To test the effectiveness of the suggested model in real scenarios, a large dataset with various diseases of apple leaves should be used.
- To incorporate the suggested mould into an approachable application that will help farmers and other agricultural experts identify and treat diseases early on.

1.2 Motivation

The agricultural sector, which is highly susceptible to plant diseases, encounters formidable obstacles in preserving crop quality and quantity. Traditional methods, including human visual examination, are labour-intensive and prone to errors. However, advancements in computer vision and deep learning provide practical means of improving the accuracy and automating disease identification. Apple output is seriously threatened by diseases such cedar apples rot, apple scab, powdery mildew, and fire blight. This project aims to develop a system that can anticipate apple illnesses using these technologies, helping apple producers identify diseases early, reduce losses, and achieve sustainability and high production.

1.3 Contribution of Research

- Novel Hybrid Model: To augment classification and feature extraction in the apple leaf disease detection procedure a new hybrid model based on CAE and CNN was developed.
- Realistic Implementation: The model was integrated into a user-friendly application that helps farmers and other agricultural specialists keep an eye on and manage apple leaf diseases.
- Superior Detection Techniques: Sophisticated modus operandi including max-pooling, dropout regularization, ReLU, and softmax activation functions were used to increase the resilience and accuracy of detection.
- Comprehensive Dataset: To guarantee the model's dependability and generalizability across a range of illness kinds and settings, a varied dataset (ALDD) was used.

The structure of this research is as follows: The literature is reviewed systematically in Section 2 of the Study. All custom and hybrid models and techniques are described in the third section of the article. In Section 4 of the paper, details about the research methodology followed are explained accompanied with pre-processing and datasets. To further detail each model, Section 5 has been allotted. Section six is the last section of the study and it focuses on conclusion and recommendations for other related research.

2 REVIEW OF THE LITERATURES

Accurate disease diagnosis is necessary to lower apple leaf infections and boosts the apple industry. Apple leaf diseases provide a challenge due to their wide range of habitats and forms. DBNet, a dual-branched detection method, addresses these problems and increases effectiveness in diagnosing diseases from challenging backgrounds with its multiscale and integrated attention branches. The identification of preferred disorders over past models serves as evidence for DBNet's sufficiency in the mentioned field [11]. An ASPP Pool module and DLV3+ semantic segmentation network are employed in a new method for estimating the severity of apple leaf disease. The performance of DeepLabV3+ model was then tested based on the optimizer, the backbone network, and learning rate with detailed analysis. Concerning the effectiveness of the proposed method in distinguishing different areas on apple leaf sores and recovering definite data, there is improved performance compared to PSPNet and GCNet. The assessment was made with respect to the optimizers, backbone network, while a comparison between the original DeepLabV3 and DeepLabV3+ was carried out in terms of the learning rate. The model attained great score such as 97. 26% Mean Pixel Accuracy (MPA) and 83. Test is the remaining 15%, Mean IoU (Intersection over Union) at about 85%. Compared with other conventional techniques of segmentations for apple leaf diseases, there has been a remarkable advancement, in both the accuracy and the diagnostic capability of disease identification [13]. The new BTC-YOLOv5s model was introduced into the study with the aim of increasing recall and accuracy of diagnosis in apple leaf diseases; the new model employed transformer, CBAM and BiFPN methods on top of the existing YOLOv5s model. The proposed model is rather accurate at a 80% level however the problems like skewed images and uneven illumination may affect the results.In order to identify apple leaf illnesses in real-time in realistic settings, this work presents the use of CNN technology with the maximum pooling and convolutional layers using Rectified Linear Unit activation functions. Our technique effectively distinguishes between healthy and diseased apple tree leaves with an astounding 91.11% accuracy on the test dataset, proving the discrimination and resilience of the model in practical applications [13]. This study looks for trends in the body of knowledge on illnesses of the apple leaf by scientometric analysis. Using scientific search methods, the study locates and assesses 214 works that were indexed in Scopus between 2011 and 2022. Automated techniques like VOSviewer and Biblioshiny are used to identify significant journals, authors, research topics, and the geographic distribution of contributions. Citation analysis, co-citation networks, and social network analysis are used to do an extensive investigation of the intellectual and social structure of the area. The research's comprehensive theoretical framework advances academic and practical understanding of apple leaf disease detection. Furthermore, it contributes to our knowledge of apple leaf disease detection by providing valuable information for future directions in this area of research [14]. The customized detection model Apple-Net, created especially for the recognition of diseases affecting apple leaves, is presented in this article. Thanks to developments like the Convolutional Autoencoder (CA) and Finite Element Method (FEM), Apple-Net outperforms YOLOv5. The feature pyramid methods of YOLOv5 are effective in improving the semantics of low-level feature maps, but they struggle to handle multi-scale data. To get over this limitation, Apple-Net uses

FEM to make multi-scale data creation more effective and CA to make detection accuracy better. Apple-Net's success in diagnosing apple leaf diseases demonstrates how well it uses cutting-edge methodologies to increase detection accuracy and reliability .The model has a mean Average Precision of 95.9% and performs better than four popular target recognition models with an accuracy of 93.1%. [15]. After being trained on the PlantVillage dataset, which contains information on apple leaf ailments such as scab, black rot, and cedar rust, the CNN performs well in disease identification. Empirical evidence demonstrates a remarkable categorization accuracy of 98% for apple leaf infections. It is interesting to note that the proposed model performs better than conventional deep CNN models in terms of execution speed and storage economy. Preliminary evidence of the system's capability of locating crop diseases suggests that it has the prospect of being used in agricultural domains [16]. In this paper, YOLOX-ASSANano, a deep learning model for diagnosing the apple leaf disease in real time is introduced. In other words, the small value of the parameter 0 means that the size of the parameter is small. 83 MB along with passing through extensive testing on the Multi-Scene Apple Leaf Disease Dataset the YOLOX-ASSANano gains an exceptional computational rate of 122 FPS. This version derived from the YOLOX-Nano architecture employs CSP-SA module, Asymmetric ShuffleBlock, and blueprint-separable convolution (BSConv) to enhance the efficiency of feature achievement and detection. This paper reported a mean Precision (mAP) of 58. 90% on PlantDoc and in the case of Trustpilot the percentage dramatically rises to 91. 08% on MSALDD and it shows a very high accuracy for most environmental condition and dataset tested. In line with this investigation, the study shows that YOLOX-ASSANano poses a possibility of being a fast and accurate way of diagnosing the apple leaf diseases as they occur in their natural environments [17]. Regarding the methodology, this study employs the VGG16 model, TensorFlow, Keras, and Kaggle Notebook for recognizing and categorizing apple leaf diseases. Since the configuration of this network makes it uncomplicated to incorporate into deep learning frameworks, the VGG16 format of this CNN is commonly used in the recognition of apple leaf disorders. Thus, with the help of deep learning techniques, the method intends to learn using the dataset that is specific to apple leaf diseases and gathered by Kaggle. It rightly categorizes many diseases that affect plants of apples, which is evidenced by the validation accuracy of 93%. 3 percent [18].This work presents VMF-SSD, or V-space-based Multi-scale Feature-fusion SSD, a novel approach to apple leaf disease diagnosis. Fast and accurate multi-scale feature representations enable VMF-SSD to identify ill patches of different sizes. The method improves detection accuracy by extracting characteristics at many scales, especially for tiny lesions. The inclusion of a V-space position branch improves texture feature and sickness spot identification even further. Attention mechanisms differentiate between cancerous patches of different sizes by independently evaluating the importance of feature channels across many dimensions. Empirical investigations [19] show that VMF-SSD runs at a detection speed of 27.53 frames per second (FPS) and achieves an average accuracy of 83.19% on the test set. This work enhances convolutional neural network (CNN) models that are previously trained to detect issues with apple crops by using digital photos from the publicly accessible PlantVillage dataset. Images of leaves with three common diseases—Black Rot, Cedar Rust, and Scab—as well as healthy leaves are included in the study. When many CNN models were evaluated for their efficacy in classifying different illnesses in apples, promising results for automated disease diagnosis in apple harvests were shown [20]. The ensemble model presented in this research uses pre-trained DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent models to classify apple tree leaves into several categories, including healthy, apple scab, apple cedar rot, and others. This work introduces a novel deep learning method that begins with the construction of a dataset that comprises annotation and data collection in order to identify and categorize apple illnesses. By initializing parameters via transfer learning, the model achieves an amazing 97.18% accuracy on the curated dataset using convolutional neural networks (CNNs), which can automatically extract features and learn complicated characteristics from raw photos. The dataset employs a range of photo augmentation techniques to improve model accuracy. The algorithm shows potential for effectively recognizing sick leaves with 96.25% validation accuracy and a 90% success rate. This research significantly advances the field of deep learning applications for apple disease detection and categorization [21].

3 METHODOLOGY

This paper outlined a method which is based on deep learning for classifying and differentiating illnesses in images of apple leaves. The designers' better pre trained CNN model layers make up the design they exhibit. The functioning of this proposed design is shown in Figure 2. This section provides a detailed explanation of the meticulous processes required to develop the model. It includes a flowchart that shows the important processes involved in this procedure.

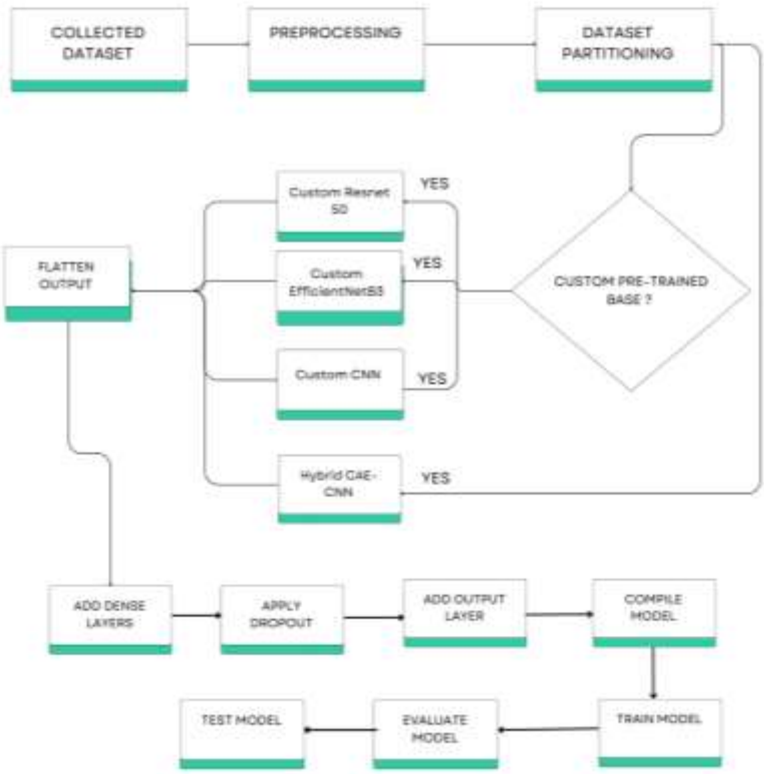


Figure 2: Proposed Model's Block Diagram

3.1 1 Dataset and Pre-processing

This research makes use of a free dataset called the "Apple Leaves Disease Dataset." A dataset must be created in order to develop a deep learning model that will categorize images of apple leaves according to whether they displayed symptoms of disease. Initially, the different class names were eliminated from the 'labels' array. Among the illnesses identified by these class names were cedar apple rot, apple curse, black decay, and a section pertaining to solid leaves. All 7771 images in the collection have a resolution of 224 by 224 pixels and are stored in RGB color channels. Subsequently, these class names were given numerical values to make sure they were compatible with machine learning methods and to facilitate model training. The scikit-learn train test split tool was used to split the dataset into distinct training and testing sets. The labels were encoded using 64-bit integers; 80% of the data was utilized for training and 20% for testing. 6,216 photos were utilized for training and 1,555 images were used for testing, according to the findings. These successive approaches set the groundwork for next generations of model creation and assessment targeted at apple leaf diseases diagnosis.

3.2 Modified Convolutional Neural Network Models

The "sequential_1" model makes advantage of a highly developed deep CNN architecture that was created especially for accurate photo classification. Complex feature extraction from input photographs is accomplished effectively by using Conv2D and MaxPooling2D layers. The network's capacity to recognize intricate patterns is improved by starting with 3x3 kernel convolutional layers that are set at 128 filters and increasing to 256 filters. By downsampling feature maps, max-pooling layers improve computational efficiency and translation-invariance. All 2D feature maps are transformed into 1D feature vectors by a flatten layer after these convolutions, readying them for use by dense layers. To enable more in-depth feature learning, four fully-connected layers with 128, 128, 256, and 324 neurons each use convolutions and linear functions. Overfitting may be avoided using carefully positioned dropout regularization, which deactivates 20% of neuron connections during training. The model's softmax activation function on a 4-neuron output layer properly assigns class probabilities. The greatest CNN architecture available, it is perfect for sophisticated photo categorization applications that need precision and nuance.

Table 2: Deep CNN Specifications for Disease Detection of Apple Leaves

Name of Layers	Size of Filter	Number of Filters	Stride	Padding	Weight	Activation
Conv2D_5	(3, 3)	128	-	Same	3584	-
MaxPooling2D_5	-	-	(2, 2)	-	0	-

Conv2D_6	(3, 3)	128	-	Same	147584	-
MaxPooling2D_6	-	-	(2, 2)	-	0	-
Conv2D_7	(3, 3)	256	-	Same	295168	-
MaxPooling2D_7	-	-	(2, 2)	-	0	-
Conv2D_8	(3, 3)	256	-	Same	590080	-
MaxPooling2D_8	-	-	(2, 2)	-	0	-
Conv2D_9	(3, 3)	256	-	Same	590080	-
MaxPooling2D_9	-	-	(2, 2)	-	0	-
Flatten_1	-	-	-	-	0	-
Dense_5	-	128	-	-	819328	ReLU
Dense_6	-	128	-	-	16512	ReLU
Dense_7	-	256	-	-	33024	ReLU
Dense_8	-	324	-	-	83268	ReLU
Dropout_1	-	-	-	-	0	-
Dense_9	-	4	-	-	1300	Softmax

This model is executed using the following mathematical expressions.

$$H^{[l]} = \text{ReLU}\ (W^{[l]} * X^{[l-1]} + C^{[l]} + b^{[l]}) \quad \text{(I)}$$
$$X^{[l]} = \text{MaxPool}\ (H^{[l]}) \quad \text{(II)}$$
$$X^{[l]} = \text{Flatten}\ (X^{[l-1]}) \quad \text{(III)}$$
$$H^{[l]} = \text{ReLU}\ (W^{[l]} * A^{[l]} + b^{[l]}) \quad \text{(IV).}$$
$$X^{[l]} = (H^{[l]}) \quad \text{(V)}$$
$$X^{[L]} = (W^{[L]} * X^{[L-1]} + b^{[L]}) \quad \text{(VI).}$$

In neural networks, Z represents pre-activation while A represents node activation. For every layers in the network, X[L] = 1/sigmoid*(H[L]) is calculated, where H and X are identified for every layer. The weight matrix W[l] and bias vector b[l], where * stands for convolution and MaxPool for max-pooling operations, are used to represent Layer l. ReLU (Rectified Linear Unit) and Softmax are utilized for activation in dense layers and the output layer, respectively, to allow multi-class classification. Dropout regularization enhances the network's resilience and prevents neurons from overfitting by deliberately introducing noise during the training phase. These elements work together to define the architecture and functionality of neural networks, which makes classification and learning tasks more effective.

3.3 Modified ResNet50 architecture

The ResNet50 architecture, which is well-known for its convolutional neural network architecture and intensive training on the ImageNet dataset, is used by the "sequential_2" model. Only the convolutional layers remain in the model when the fully connected layers are removed using {include_top=False}. These layers are skilled at effectively extracting hierarchical information from input photos. The ResNet50 framework produces 2048 7x7 feature maps with an output size of (None, 7, 7, 2048). In order to integrate these three-dimensional maps seamlessly with later dense layers, they are flattened into a linear vector. ReLU activation functions over layers of 128, 128, 256, and 324 neurons, respectively, add non-linearity and improve feature representation. After the fourth dense layer in training, a Dropout layer with a 0.2 dropout rate randomly deactivates neurons to avoid overfitting. The output layer uses a softmax activation function to provide probabilities for each of the four classes in the multi-class classification job. ResNet50 is distinguished by its deep layers, which support its strong feature extraction capabilities and adaptability.

Table 3: Specifications of ResNet 50Model

Layer Name	**Output Shape**	**Parameters**
resnet50	(None, 7, 7, 2048)	235,87,712
flatten_2	(None, 100352)	0
dense_10	(None, 128)	128,45,184
dense_11	(None, 128)	16,512
dense_12	(None, 256)	33,024

dense_13	(None, 324)	83,268
dropout_2	(None, 324)	0
dense_14	(None, 4)	1,300

$H^{[1]} = \text{ResNet50}(X)$ (VII)

$X^{[2]} = \text{Flatten}(H^{[1]})$ (VIII)

$H^{[3]} = \text{ReLU}(W^{[3]} * X^{[2]} + b^{[3]})$ (IX)

$H^{[4]} = \text{ReLU}(W^{[4]} * H^{[3]} + b^{[4]})$ (X)

$H^{[5]} = \text{ReLU}(W^{[5]} * H^{[4]} + b^{[5]})$ (XI)

$H^{[6]} = \text{ReLU}(W^{[6]} * H^{[5]} + b^{[6]})$ (XII)

$X^{[7]} = \text{Dropout}(H^{[6]})$ (XIII)

$X^{[8]} = \text{Softmax}(W^{[7]} * X^{[7]} + b^{[7]})$ (XIV)

The above formulas outline the step-by-step processes of a neural network, starting with ResNet50 feature extraction. The features are then flattened and passed through many thick layers with ReLU activated after that. In order to avoid overfitting, dropout regularization is used. Softmax activation is used in the last layer to calculate class probabilities. The neural network framework's feature extraction and classification are successfully made possible by this design.

3.4 Modified EfficientNetB3

Any Convolutional network may be used for feature extraction; EfficientNetB3 is utilized in this instance. The model, called "sequential_3," is very effective at extracting complicated characteristics from input photos as it has been pre-trained on a large image dataset. This basic network's output form is (None, 7, 7, 1536), which represents 1536 7x7 feature maps. Since dense layers can only link to a single input layer, this output is then routed via a Flatten layer, which turns the feature maps into a one-dimensional vector. The first two dense layers have 128 neurons each, the third has 256 neurons, and the fourth has 324 neurons. These layers come after the Flatten layer. By introducing non-linearity via the application of the ReLU activation function, these thick layers allow the model to capture intricate patterns. After the fourth thick layer, a dropout layer with a dropout rate of 0 appears that indicating that no dropout regularization is employed. The softmax activation function is used in the output layer to provide class probabilities for precise multi-class classification. Its four neurons match the quantity of classes in the order work. Even without dropout regularization, the model's combination of dense layers and EfficientNetB3 provides significant feature extraction capabilities and classification accuracy, making it suitable for a variety of image classification applications.

$H^{[1]} = \text{EfficientNetB3}(X)$ (XV)

$X^{[2]} = \text{Flatten}(H^{[1]})$ (XVI)

$H^{[l]} = \text{ReLU}(W^{[l]} * X^{[l]} + b^{[l]})$ where $l=3,4,5,6$ (XVII)

$X^{[7]} = \text{Dropout}(H^{[6]})$ (XVIII)

$X^{[8]} = \text{Softmax}(W^{[7]} * X^{[7]} + b^{[7]})$ (XIX)

EfficientNetB3 utilizes the brain network model to straighten input photographs and concentrate highlights for additional handling. Dense layers generate intermediate outputs by combining ReLU activation with linear transformations. Overfitting is decreased with the utilization of dropout regularization in the final output layer. The probability of each class is calculated using softmax activation. When combined, these techniques enable the design of a neural network to efficiently extract and classify features.

3.5 Proposed Algorithm

Input:
Training Dataset, $D=\{(xi,yi)\}$ni=1
Load:
Base learner M1: Pre-trained ResNet
Base learner M2: Function uses pre-trained EfficientNet
Base learner M3: Algorithm 1 (CNN)
Base learner M4: - Attached model
Meta learner M5: XGBoost()
Meta learner M6: LightGBM().
Begin
Step 1: Train base classifiers
1. In the loop from $t \leftarrow 1$ to 4 (train ht on D),

Train base learners Mton Dataset D to obtain$h$t
End for
Step 2: Feature extraction and stacking for the Dataset
2. For i←1i←1 tondo
Depending on t, which will have values between 1 and 4, include the following:
Compute$h$t (xi) # to extract features from the xi, use ht
End for
where xi'={ $h1(xi)$, $h2(xi)$, $h3(xi)$, $h4(xi)$} Db←{xi',yi}
End for
Step 3: Train Meta classifier
3. If meta-learner is XGBoost() then
$h5$: train $M5(Db)$
Output: Classification Result
4. If meta-learner is LightGBM() then
$\boldsymbol{\alpha}\beta cDnew$ ← merge($M4(D)$) t=1 2 3 4
$h6$: train $M6(Dnew)$
Output: Classification Result
End

3.6 Proposed Hybrid Convolutional Autoencoder - Convolutional Neural Network model

Convolutional autoencoder and convolutional brain organization, are incorporated together to form the blended model known as CAE-CNN. The input photos of size 224 x 224 pixels are passed to the CAE component of the network first. It consists of one stradding of three layered convolution base with three color channels in each layer. Specifically, the first layer is the convolution layer that applies 'same' padding, rectified linear unit as the activation function and 32 filters of size 3x3, for the spatial aspect of the input. Following this, we have a max pooling layer with the 2 x 2 windows. In a step-by-step manner, there are fewer filters, which are provided in more max-pooling layers and later in convolutional layers, resulting in a deeper pyramid of the given input data. The output of the CAE component is fed into CNN as the input, but the dimension of the input reduced to 32x32x8. The CNN portion consists of many layers with step up sides of (3,3), as well as a number of CV layers accompanied by 'same' padding and ReLU enactment abilities to decrease dimensionality additionally. These layers exclude the level components that are beyond doubt in the CAE's depictions and, subsequently, the output is flattened and is passed through the two dense layers having ReLU and softmax activation for the final classification of each of the four classes. It uses a number of convolutional layers of increasing decision-making that segregate and identify the highlight. This is followed by input images of 224x224 with three variety channels as the starting point.

4. RESULTS AND DISCUSSION

The Apple Leaf Disease Dataset's 224x224 RGB pictures are used to train and assess unique deep CNN models. 20% of the dataset is reserved for testing, while the remaining 80% is used for training. It is important to keep in mind that assigning numerical labels (0, 1, 2, and 3) to the four classes is just a temporary fix; categorical labels should ideally take its place in order to correctly create the model. In order to get precise classification in several categories, SVM training is further used to images of apple leaf disease. This methodical approach ensures that the models achieve high levels of accuracy and reliability when it comes to identifying and classifying various types of apple leaf diseases.

4.1 Experimental Setup

The Seaborn, Imutils, Keras, and Scikit-learn packages are used to build the customized models on the Kaggle virtual platform. An Intel(R) Celeron(R) CPU N2840 @ 2.166GHz processor with 4GB of RAM powers the environment. The misfortune capability that is utilized to survey the multiclass order issue is unmitigated cross-entropy. At a learning rate of 0.05, ten training epochs are completed.

4.2 Performance Evaluation Metrics

Four main measures are used to evaluate the proposed model and certain pre-trained models: F1-Score, Validation Accuracy, Precision (sometimes called Positive Predictive Value, or PPV), and Recall. Confusion matrices are provided with every model to offer insights into its performance and enable in-depth research. The pre-trained models also come with graphs that show the link between Accuracy and Epochs, which graphically represent the models' training progress and performance over time. These thorough assessments provide a thorough grasp of each model's skills and efficacy for the intended purpose.

Accuracy is a metric that quantifies the ratio of accurate detections produced by a research model to the total number of detections made [18].

$$Accuracy = \frac{No.of\ correct\ detections}{total\ no.of\ detections} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(i)}$$

Precision was obtained by taking the total number of correct observations of the positive class divided by the total number of observations that the classifier put in the positive class. [18]

$$.Precision \ = \frac{True_{pos}}{True_{pos}+False_{pos}} \text{ .... (ii)}$$

Recall is the number of instances that are correctly predicted to be of class 1 with respect to all instances that are actually of class 1. [18].

$$Recall \ = \frac{True_{pos}}{True_{pos}+False_{neg}} \text{ .... (iii)}$$

F1-Score is a single statistic that balances accuracy and recall for assessing a classifier's performance. It is calculated as the harmonic mean of precision and recall.

$$F1 - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \text{ .... (iv)}$$

4.2.1 Visual Representation of All Models

An architecture diagram shows how a deep learning model or neural network is put together and how its data flows. Usually, it begins with an input layer that represents input pictures, such as custom conv2d_5_input (None, 224, 224, 3). Next, layers for flattening, dense, dropout, convolutional, and max pooling are applied to the data. The input and output tensors of each layer show how the network handles data. Convolutional and pooling layers gradually decrease the height and breadth of feature maps as the channel depth rises. Deep layers are used to examine flattened vectors for tasks involving regression or classification. Data flow is streamlined, and information processing and interpretation inside the network are made easier by this architectural design. The figure 3 elaborated the working of model.

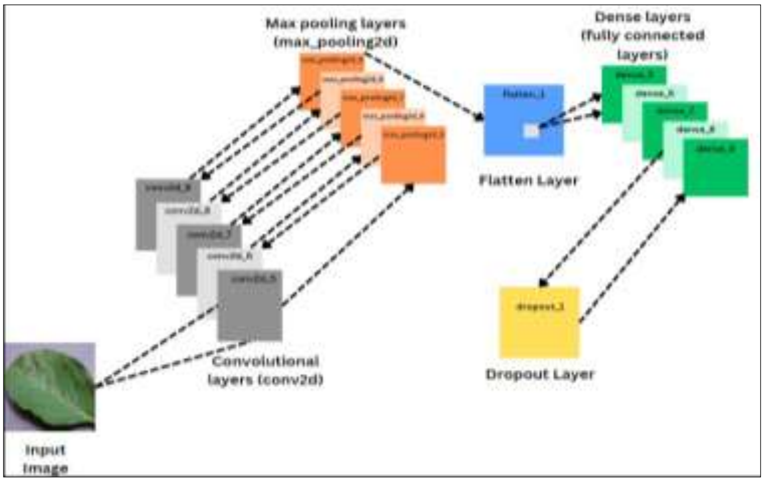


Figure 3: Custom CNN model Graphical Representation

An extraordinarily prepared ResNet-50 model fills in as the element extractor in the profound learning model design that is shown in figure 4. For characterization or relapse undertakings, a progression of thick layers and a dropout layer are utilized after the ResNet-50 layer. A three-layered picture tensor of the structure (None, 224, 224) is the info. This tensor is processed, flattened, and fed through numerous dense layers by the ResNet-50 layer to produce outputs of various sizes. The final dense layer generates a prophecy or score tensor of the form (None, 4) for a four-class multi-class classification problem.

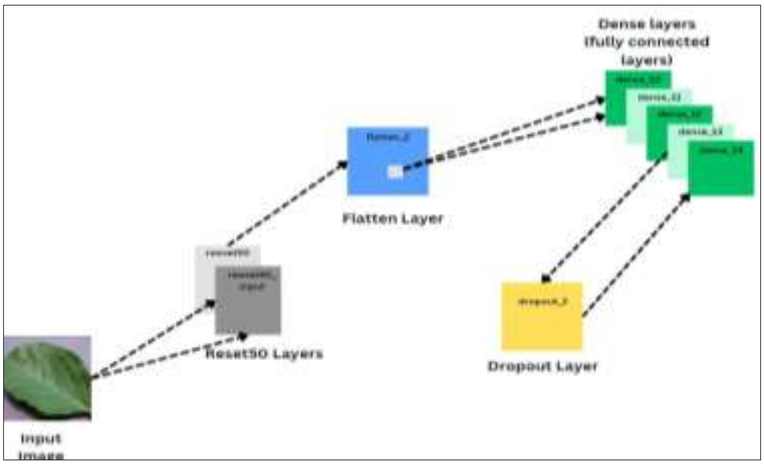


Figure4: Custom ResNet-50 Graphical Representation

The input layer of the neural network architecture is intended for the classification of images. To extract features inside this framework, a modified EfficientNet model is used. The flattened attributes are processed via deep layers with dropout to avoid overfitting after feature extraction. Four classes are given separate classification probabilities in the last dense layer. Accurate picture categorization is ensured by this mix of layers and specially designed pre-trained algorithms. The figure 5 described the working of model.

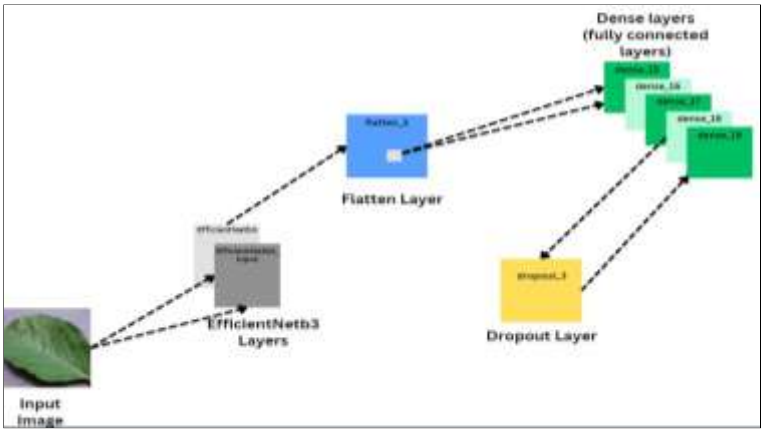


Figure 5: Custom EfficientNetb3 Graphical Representation

The model is a multi-layered sequential convolutional neural network (CNN) containing features intended for classification and feature extraction. The ReLU activation functions are applied after every Conv2D layer. MaxPooling2D layers are inserted between these convolutional layers to gradually lower the spatial dimensions of the feature maps without sacrificing important information. The three-dimensional feature maps are converted into one-dimensional vectors by a flatten layer, which comes after many convolutional and pooling layers. After that, this vector passes through two thick layers that are entirely coupled before arriving at an output layer with four units. The accuracy of picture categorization is improved by this hierarchical structure, which makes feature extraction simpler. The model is represented by figure 6.

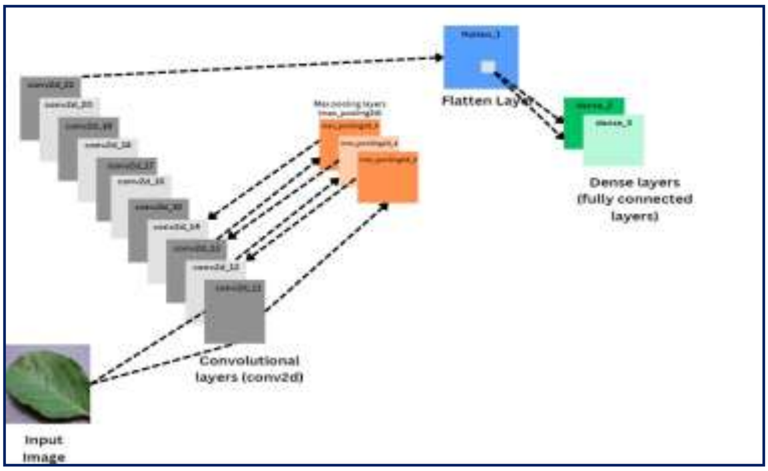
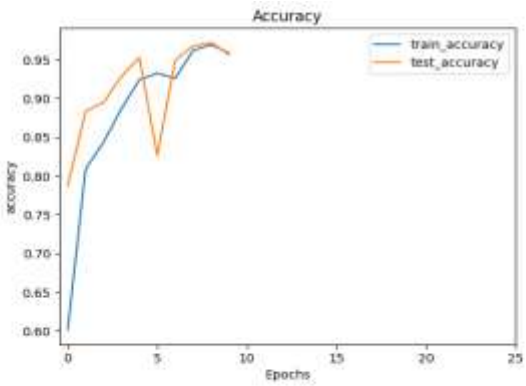


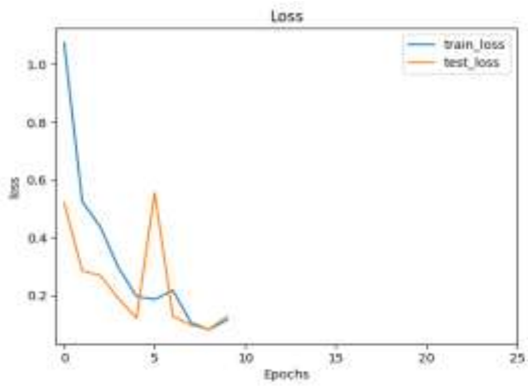
Figure 6: Hybrid Model Graphical Representation

4.2.2 Proposed Models Accuracy versus Loss Analysis

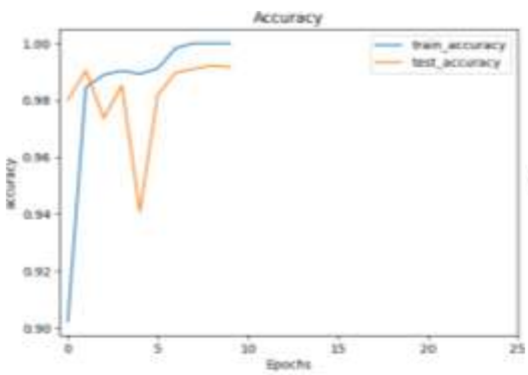
Loss versus accuracy representation of proposed models are shown in figure 7(a),7(b),7(c),7(d),7(e),7(f),7(g) and 7(h). On the left hand side the figures describes the Loss of Custom Convolutional Neural Network Models, Custom ResNet50 architecture, Custom EfficientNetB3 and Proposed Hybrid Convolutional Autoencoder - Convolutional Neural Network model. On the right hand the accuracy graph are described of Custom Convolutional Neural Network Models, Custom ResNet50 architecture, Custom EfficientNetB3 and Proposed Hybrid Convolutional Autoencoder - Convolutional Neural Network model.



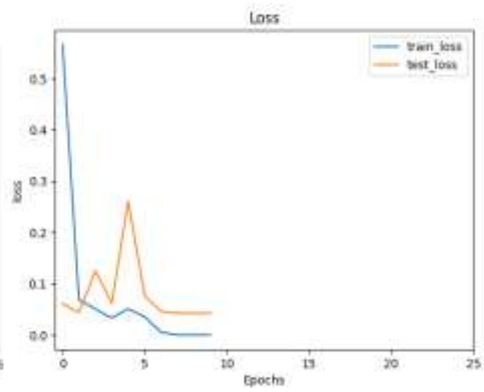
(a)



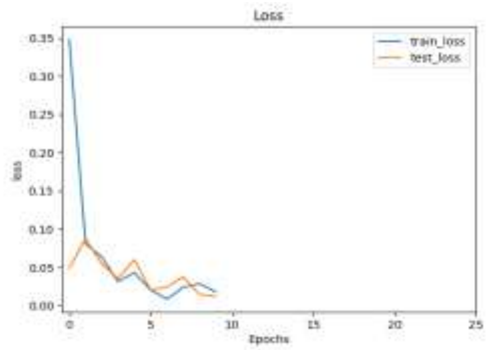
(b)



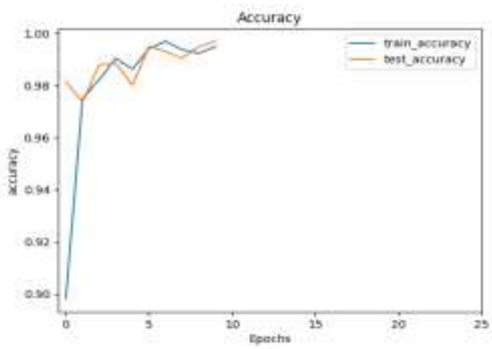
(c)



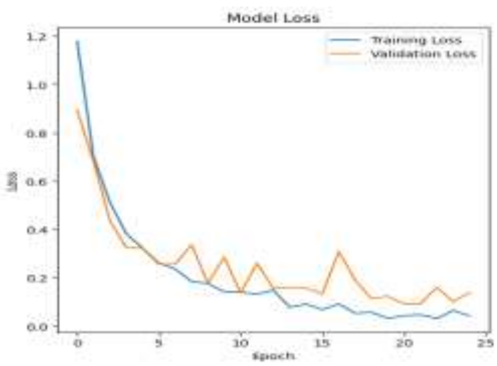
(d)



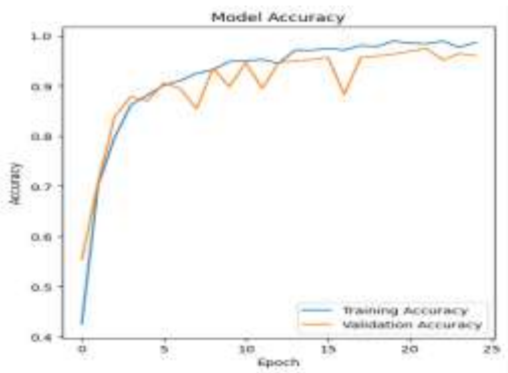
(e)



(f)



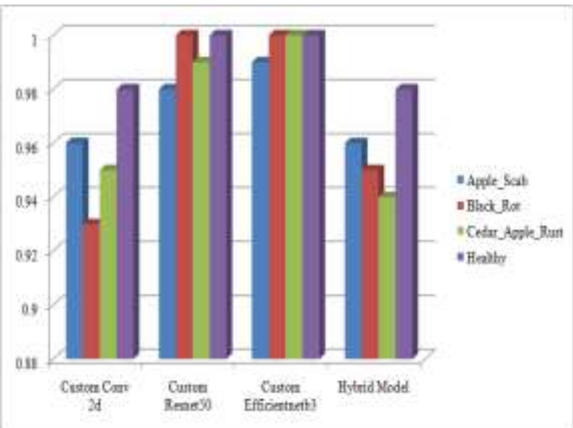
(g)



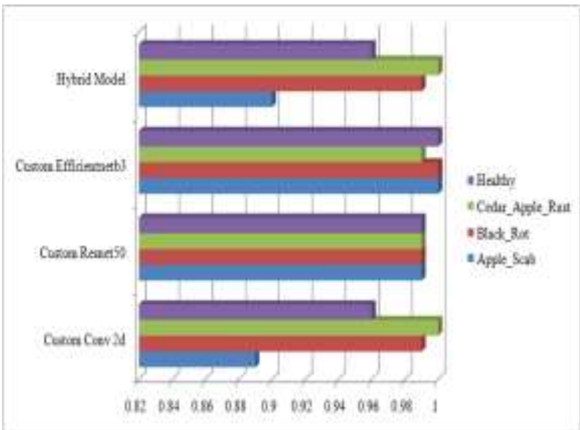
(h)

Figure 7: Accuracy versus Loss curves (a)(b) Modified conv2d, (c)(d) Modified ResNet-50, (e)(f) Modified EfficientNetB3, (g)(h) Proposed Hybrid Model

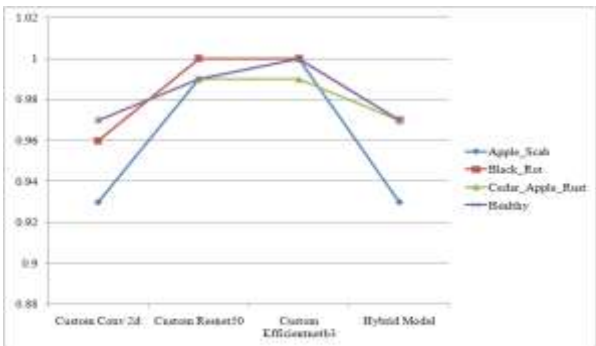
4.2.3 Model Performance Comparison based on Performance Metrics



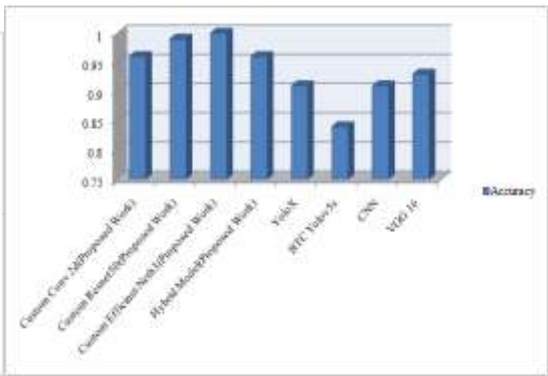
(a)



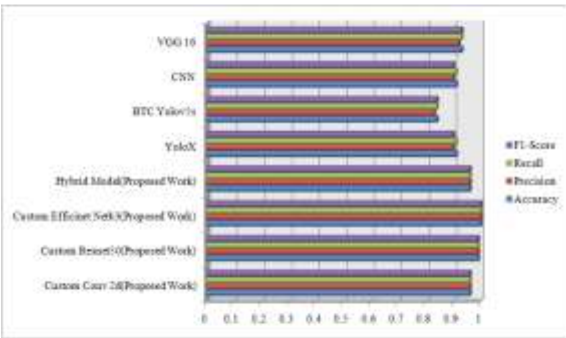
(b)



(c)



(d)



(f)

Figure 8(a)(b)(c)(d)(e)(f): Performance Matrices Evaluation

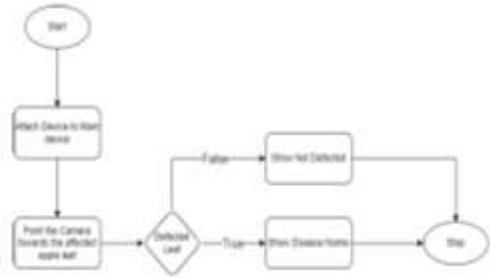
4.2.4 Performance Analysis of Proposed Hybrid Model with SOTA

The comparison of our proposed model has been defined by the table 4 with all possible parameters.

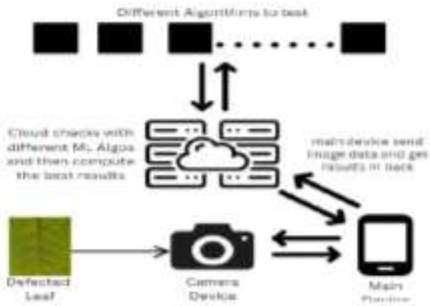
References	Technique	Leaves	Dataset	Result(Accuracy)
[17]	You Only Look Once X	Apple	CALD	91%
[22]	Binary and Ternary Convolutional YOLOv5 Small	Apple	DocPlant	84.3%
[13]	Convolutional Neural Network	Apple	Apple Tree Leaves	91.11%
[15]	YOLOv5	Apple	Baidu PaddlePaddle's ALD	95.9%
[18]	Visual Geometry Group 16-layer network	Apple	Apple Leaves Disease Dataset	93.3%
[19]	Visual Modality Fusion Single Shot Multi Box Detector	Apple	Apple Leaves Disease Dataset	83.19%
[21]	Convolutional Neural Network	Apple	Plant Pathology and Plant-Microbe Biology ALDD	90%
[23]	K-Nearest Neighbours	Apple	Apple Leaves Disease Dataset	73%
[24]	Deep Convolutional Neural Network	Apple	CDRD	94.74%
[10]	Deep Convolutional Neural Network	Apple	Apple leaf image data set	92.29%
Proposed work	Modified Convolutional Neural Network	Apple	Apple Leaves Disease Dataset	96%
	Modified Resnet50	Apple	Apple Leaves Disease Dataset	99%
	Modified EffiecientNetB3	Apple	Apple Leaves Disease Dataset	100%
	Hybrid CAE-CNN Model	Apple	Apple Leaves Disease Dataset	96%

5. ADVANCED AGRICULTURAL DISEASE DIAGNOSIS SYSTEM

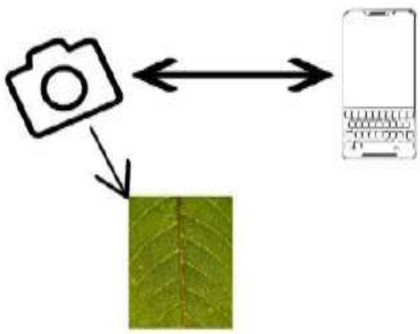
An innovative method for identifying illnesses in apple plants is presented in the patent application, "Method and System for Automated Classification of Apple Leaf Diseases Utilizing an Ensemble Deep Learning Model." This invention improves apple leaf disease diagnosis and classification by using ensemble deep learning. This approach gives farmers a better tool for disease prevention by using cutting-edge machine learning models and algorithms to assess digital photos of apple leaves in a dependable manner. The suggested method seeks to increase crop health assessments' accuracy and mitigation techniques' efficacy, hence enhancing agricultural output and sustainability. The working of our patent model is defined by the figure 9.



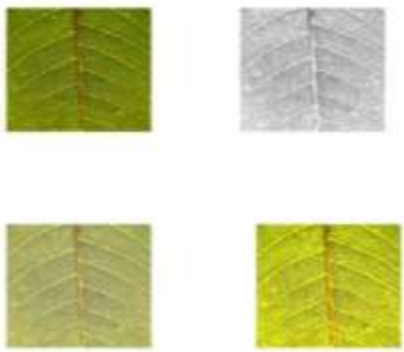
(a)



(b)



(c)



(d)

Figure 9(a)(b)(c)(d): Real-time Deployment Process of Proposed Model

Conclusion and Future Work

In summary, our work improves agricultural disease detection, especially for illnesses of the apple leaf. Using Conv 2D, ResNet50, and EfficientNetB3 convolutional neural networks, we created and evaluated hybrid models. These techniques use deep learning-based computer vision to automatically categorize images of apple foliage and detect illnesses. The Apple Leaves Disease Dataset is used in our work to show that the EfficientNetB3 model achieves 100% accuracy rate, underscoring the revolutionary potential of deep learning in agricultural disease prevention. In the end, our work improves and automates disease identification, giving farmers and other producers the means to lower crop losses and boost output. As cutting-edge agricultural technology develops further, it has the potential to greatly increase global food security and sustainability programs.

Declaration

Declarations must be presented in a certain format according to some publications requirements. To determine if you must fill out this area, please refer to the journal's Instructions for Authors. If so, the following parts under the category "Declarations" in your book are required:

Funding:This research did not receive a specific grant from any nonprofit, public, or private funding source.

Conflict of interest/Conflicting :interests (check the journal's particular requirements for the correct heading to use)) NA

Ethics Approval :Yes

Consent for participation :Yes

Consent to publication :Yes

Data and materials Availability :Not applicable

Availability of Code :Not applicable

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.

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