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Research Article

Tomato Leaf Disease Detection by Hybrid AI and Ml Technology

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Abstract: Diseases that affect plants contribute to productivity decline, but they can be managed with ongoing monitoring. It is time-consuming and prone to error to track plant diseases manually. Early disease detection using Artificial Intelligence (AI) and machine vision can lessen negative impacts while also overcoming some of the limitations of continuous human monitoring. Therefore, this study uses both Deep Learning (DL) and Machine Learning (ML) to classify normal and unhealthy tomato leaf images in order to recognize disorders of tomato leaves. It then proposes a way for extracting features from deep, lighter-weight CNN designs and transferring them into conventional ML classifier using methods based on transfer learning. Support Vector Machine (SVM) classifier, CNN pretrained model Inception ResNet V2 for feature extraction, and a modified U-Net segmentation model make up this hybrid system. Utilizing an open-source database (Plant Village), the proposed model can at the start, but not exclusively, detect nine distinct tomato diseases. With 97.87% accuracy, 0.96 precision and 0.94recall respectively, the findings are very promising. The proposed approach demonstrates how it is better than the existing techniques. The excellent outcome shows the potential of CNN-based techniques for tomato disease diagnosis in both field and laboratory settings.

Keywords: Machine Learning, Deep Learning, CNN, SVM, Classification, Leaf Segmentation, Plant Disease, VGG16, AlexNet, ResNet152, InceptionResNet V2

Introduction

Back thousands of years ago, agriculture helped domesticate many of the main food plants and animals we consume today. Agriculture has been heavily commercialized, which has had a negative impact on the ecosystem. The detection of plant diseases is one of the greatest issues in agriculture. One of the main global issues that humankind is currently facing is food insecurity (Chowdhury *et al*., 2020), which is a significant contributor to plant-borne illnesses. Research found that plant diseases are responsible for about 16% of the world's lost crop yields (Oerke, 2006). Early disease detection aids in stopping the spread of the illness to other plants, avoiding significant financial losses. Diseases of plants can cause a range of problems for the agriculture-based economy, from mild indications to the destruction of entire plantations. (Savary *et al*., 2012).

One of the most significant and commonly consumed crops globally is the tomato (Solanum Lycopersicum L). Next to potatoes, it is the second-most significant vegetable product (Home Food and Agriculture Organization of the United Nations, 2019). Various leaf diseases that affect healthier tomato plants can result in lower or lower-quality yields, which can eventually have an impact on people's health, way of life, and financial security. These leaf diseases seriously reduce tomato crop fruit output. Therefore, reducing yield losses and ensuring optimal production will be made possible by early and precise diagnosis and classification of tomato leaf disease.

Plant tissues are visually inspected by trained specialists who then classify plant leaf diseases based on their findings. This technique has a difficult issue that is expensive, time-consuming, and ineffective. Numerous studies have demonstrated that automated plant disease identification can solve this issue (Azlah *et al*., 2019).

Sensors, automation, connectivity to the Internet, and Artificial Intelligence (AI) are all used in "smart agriculture". The subject of smart agriculture has many applications, including smart irrigation, farming equipment, disease identification in open fields, and microclimate management, environmental control, and commercialization process in smart greenhouses. The platform in use determines what needs to be done to solve the problems based on the ones that have been identified. In an attempt to enhance the plant disease detection process, new technologies like Artificial Intelligence (AI) and Computer Vision (CV) are required.

Generally, it is highly impossible for farmers to identify the exact disease instantly. Therefore, it is certainly necessary to identify the disease accurately at its early stage in the area of precision agriculture (Islam *et al.*, 2024). However, there are still many gaps are remaining yet in accurate disease identification. Blind pesticides by farmers will increase the economic losses (Kumar *et al.*, 2023). Thus, these challenges of plant disease identification with image processing methods are a hot research topic. When crop plants are damaged by diseases, the country's production and its economy are also affected (24).

Even though, the traditional image processing techniques has given certain results with high precision in the identification of diseases, but still there are some obstacles and limitations remain. Such as time-consuming works in collecting samples and getting that into lab for testing, in addition the cost for shipping and buying high-equipped testing equipments. These are the factors that motivates this research.

Computer technology, which includes Machine Learning (ML) and Deep Learning (DL) techniques, has now replaced the conventional disease diagnosis tools for tomato leaves. The disease diagnosis and control methods offered by these computer technologies are, however, more effective and convenient. Recent years have seen a significant increase in the use of traditional ML approaches in machine vision for automating the categorization of plant diseases (Ngugi *et al.*, 2021). Conversely, the traditional machine learning techniques rely heavily on the features one can offer it. The above methods are laborious and demanding because the aforementioned characteristics must be laboriously retrieved by a specialist. The drawback of the approach using handcrafted features can be readily overcome by automated feature extraction using DL. DL is widely used for classifying plant diseases because it outperforms conventional ML (Hasan *et al.*, 2020). The technique that is frequently utilized for classifying plant diseases is a deep Convolutional Neural Network (CNN), which requires a large amount of training data and a lot of work. Deep learning is also a greater expense compared to standard ML methods in terms of processing capabilities.

These AI techniques still require specialized feature extraction and segmentation techniques in order to be completely effective and error-free. We were inspired to write this paper as a result of the significance of creating an effective disease classification framework to accurately recognize and categorize the sort of disorder at its earliest phases. There hasn't been much study on segmenting imagery of leaves from the underlying environment, despite the fact that disease classification and detection in tomato as well as other plant leaves have been widely studied. Because lighting conditions in real-world images can vary greatly, more effective segmentation methods can help AI algorithms in learning from the proper area of interest instead of the scenario.

In order to distinguish between nine diseases affecting tomato plants, this paper suggests an effective hybrid classification method. Three distinct technologies make up the developed system: The U-Net model for segmentation is the first component, followed by light-weight pre-trained prototypes used as a stable fixed feature extractor and shallow classifier training as the third component. Therefore, the following elements of this paper are its primary contributions:

- Designing an effective system for classifying and identifying tomato leaf diseases using a tailored CNN model and SVM strategy
- For image features used for plant disease classification, three cutting-edge CNN pre-trained models VGG16, ResNet152, and hybrid CNN consisting of InceptionResNet V2 are compared
- Examining the effectiveness of the proposed hybrid approach employing a database of tomato leaves

Related Works

Plant Pathogens

Food insecurity, which plant diseases are a big contributor to (Strange and Scott, 2005), is one of the most significant global issues currently confronting humanity. One estimate places the worldwide crop yield loss attributable to plant diseases at about 16%. The major categories of pathogens in plants include fungi, bacteria, viruses, algae, and plants that are parasitic. A significant food crop grown all over the world, tomatoes account for 15% of the typical global vegetable consumption. Like other plants, tomatoes can be impacted by climatic and environmental factors, and they can contract illnesses.

In addition to viruses, bacteria and fungi can also trigger tomato diseases. Plants can become infected by fungi from a variety of sources, including contaminated seeds and dirt. The typical symptom of fungal diseases is a tiny water-soaked spot on a tomato leaf, which quickly develops into a round spot with a diameter of 0.3 centimetres (Gleason and Edmunds, 2005). Another significant plant disease is bacteria. Bacteria enter plants through stomata, which are naturally occurring openings, in addition to by means of incisions like insect stings, cuts, and pruning. Weather conditions that are hot and rainy encourage the spread of bacterial illnesses. Molds are a major contributor to plant disorders, and a few of their telltale symptoms is the appearance of dark-colored, inconsistent blemishes on the pointed ends of leaves and plant stalks. It is crucial to identify tomato leaf diseases as soon as possible in order to cure the plant. The following are a few tomato leaf diseases.

Early Blight

The foliage can be impacted at any stage of development by this common tomato disease. Because the fungus feeds on the vegetation, it causes blight and typical leaf spots. The first indications of early blight on plants are smaller, black scarring, mostly on older foliage. By the time spots are one-fourth of an inch or larger, a bull's-eye arrangement of concentric circles is visible at the center of the diseased region.

Late Blight

The fungus Phytophthora infestans is the source of the rapidly proliferating tomato plant disease, which manifests itself during cool, rainy spells that may occur toward the end of a growth season. The irregular green-black splotches on the foliage resemble frost damage. Large, atypically shaped brown blotches on fruit that rapidly turn rotten are possible. Potatoes can spread this plant disease to other plants, which also effects them.

Yellow Leaf Curl

Rather than seeds, whiteflies transmit the virus that causes tomato yellow leaf curl. The fruit yield of tomato and pepper plantations seems severely harmed by this illness. Whiteflies may spread the disease from nearby infected weeds like jimsonweed and different nightshades. Tomato plants may go up to two to three weeks without showing any symptoms after an infection.

Leaf Mold

Mold on leaves is brought on by the fungi Passalora fulva. It first becomes apparent on older leaves near to the soil's surface, where there is poor airflow and excessive dampness. The first indications are small, expanding spots of pale green or yellowish color on the top surface of the leaf that eventually turn an unusual yellow. When it's humid outside, the fungus's spores develop in a gray, velvety growth that covers the spots on the lower leaf surfaces. When the infection is bad enough, the spots congregate and the vegetation dies. The fungus can occasionally target fruits, blossoms, and stems. On the stem end of ripe and green fruit, a black, leathery rot is possible.

Mosaic Virus

The mosaic virus commonly affects tomatoes and affects numerous plant species. Despite not killing the plant, mosaic virus reduces the quantity and grade of fruits. The light green and golden mottling and markings on the leaves and fruits of plants affected by the virus give it its name. Additionally, leaves can develop into fern-like shapes that are uneven.

Literature Review

Saleem *et al*. (2020) presented an in-depth analysis of various latest DL structures, classified into three sections: Well-known, modified, along with cascaded variants. Further efficiency improvements were made to the best-obtained versions by utilizing different DL optimization techniques. Improved GoogLeNet, AlexNet along with GoogLeNet and Xception were determined to have the finest accuracy in validation followed by F1-scores across each category. Whenever all of these algorithms underwent training by multiple DL optimizers, the version of Xception trained by the Adam optimizer achieved the highest F1-score. This suggests that the model generated by CNN alongside the optimization algorithm combined reflect the classification of the plant disorders that is most suitable.

Using a well-known DL technique, the CNN, Sareen *et al*. (2022) sought to identify the early blight condition in tomato plants in advance in order to avoid the plants from becoming seriously impacted in the early point. This creates a disease forecasting model using an image-based dataset for the Tomato Early Blight Disease (TEBD). A number of image processing techniques, such as the process of segmentation augmenting, changing the size, de-noising, and eliminating the background, were used to produce a polished dataset. The updated TEBD dataset and the CNN training method were also used to build a visual based TEBD forecast system. The impacts of hyperparameters like epochs as well as mini-batch size were also investigated for a range of train-test combinations.

A hybrid CNN-RNN classifier for detecting tomato plant diseases was described in David *et al*. (2021), along with the model's application and performance evaluation. Then, label-binarizer is used to segment the picture. Each image's pixels are captured in order to extract its features. Each CNN based Xception and RNN algorithm receives the feature values. In order to multiply the results of the CNN and RNN classifiers, element-wise multiplication is used. The product then moves into the thick layer. Early discovery is enabled by the high predictive rate of time series observations. The suggested model had the highest categorical accuracy for disease categorization at 98.25 percent. Additionally, the hybrid CNN-RNN design requires less computational work.

To determine which method performs best at disease detection, citrus leaf disease is classified in Sujatha *et al*. (2021) using both ML (Stochastic Gradient Descent, SVM, Random Forest) and Deep Learning (VGG-16, VGG-19, Inception-v3). A technique for classification issues is the application of stacked cross-validation with a factor of 10, that selects the patterns of folds so that each fold has approximately identical proportions of the target class. The system forecasts the type of disease and aids in taking action before the plants become more harmed when fresh images are provided as input.

In the study by Sahu *et al*. (2023), seven well-liked DL models were employed to categorize tomato leaf illnesses. To adjust the chosen models to the particular job of classification, deep feature extractions as well as fine-tuning techniques were used. The features were acquired using deep feature extraction, and completely connected layers concerning CNNs were used to classify them. Utilizing image information that was acquired from the Institute for Agricultural Research located in India, the experiments were carried out. The 155 images in the collection are pictures of healthy and diseased tomato leaves. To expand the collection, data enhancement was employed. So as to eliminate the backdrop and emphasize the deep features, three segmentation algorithms were also used. The evaluation's findings demonstrate that using image segmentation methods in combination with deep feature extraction led to better outcomes (up of about 100% accuracy) than doing so alone.

A variety of machine learning techniques use the images taken by portable cameras or by drones to detect the diseases. Before using machine learning methods for identifying diseases, such methods require feature extraction from the pictures. A deep learning architecture that autonomously extracts features in a hierarchical fashion is suggested in Aggarwal, (2022). Based on a variety of geometric and illumination settings, features are extracted. The Harris corner detector, SIFT, and SURF are the most widely utilized feature point detectors and identifiers. Using neural networks, the characteristics are categorized into three groups to classify the leaves: healthy, bacterial spotted, and Septoria leaf spotted. Accuracy is used as the performance measure to gauge the model's performance.

Deep CNN models like mobile Net and ResNet CNN are used in Ramya *et al*. (2022) to explain a real-world approach to identify tomato leaf illness. Performance of deep neural networks can be improved by adjusting pooling configurations and hyper-parameters on a mechanism. The pre-trained framework is deployed onto one microcontroller running PIC using a neural compute stick made of specific CNN hardware components. TTL is used to link the output from the PIC microcontroller and the program written in MATLAB functioning on the computer. Data is transferred from the PIC toward the computing platform, in which it is displayed on a page on the internet, using the ESP8266 IoT module, which is loaded with an embedded C program.

The main goal of Kumar *et al.* (2023) is to identify the virus in tomato leaves more quickly and accurately using deep CNN and various residual networks. Using cloud-based MATLAB and a pre-trained CNN with a residual framework, it classified the illness found inleaves of tomato plant. The collection of tomato leaves used in the experiments includes one healthful tomato leaf class and six distinct kinds of diseases. After examining a number of results, they have come to the conclusion that, for the same dataset in the cloud, ResNet-50 exhibits better precision for fifty percent training and fifty percent testing of statistics, and ResNet-18 exhibits higher efficiency for training and testing ratio as seventy and thirty percentage of data.

Kaya and Gürsoy (2023) put forth a brand-new approach for DL-based identification of plant illnesses that combines RGB and segmented images. Two images were used as the input for a multi-headed DenseNet led design that was created. It tested the model using the 54183 images and 38 groups from the Plant Village dataset. The average accuracy, precision, recall, as well as f1-score for the fivefold cross-validation method were 98.17, 98.16, 98.17 and 98.12%, respectively. The suggested method uses image fusion to distinguish between numerous plant diseases with distinct traits. The reliability of the model is demonstrated by the significant rate of success and low standard deviation, and the framework is capable of being incorporated into plant pathogens identification as well as prompt notification systems.

Baser *et al.* (2023) uses four layered CNN followed by max pooling layer and reduced the dimensions of the image to 150x150. However, its accuracy will be reduced if the images were captured under uncontrolled environment. Therefore, there is a need of a model that has efficient preprocessing techniques.

Kumar *et al*. (2023) used deep CNN and limited to only six types of disease classification. Classification for more disease identification is needed in current situation that should truly help the farmers. Gangadevi *et al.* (2024) uses hybrid fruit fly optimization that relies on simulated annealing optimization SVM. However, due to lack of effective preprocessing techniques it had achieved only 91.1% of accuracy. It also needs good preprocessing techniques. Above-mentioned drawbacks are rectified in the proposed model.

Methodology

A CNN framework trained on images of diseased tomato leaves is used to create a hybrid AI model that is efficient and beneficial for distinguishing tomato diseases.

Dataset Description and Data Preparation

The images used are part of the Plant Village database (Hughes and Salathé, 2015) and related foliage mask dataset (SpMohanty/PlantVillage-Dataset, n.d.), which includes 18,161 pictures of tomato leaves and associated foliage masks with segments. Although there are many different plants in the dataset, we settled on the tomato as the basis for this study's leaf segmentation and classification model training. Ten distinct classes comprise the data; nine of these classes correspond to different tomato diseases, and the tenth class is comprised of healthy tomato leaves. The data consist of a set of 256x256 RGB pictures of tomato leaves. Based on their image classifications, healthy and infected leaves can be distinguished. It was made sure that each picture had a single centroid leaf during the photo shoot. Additionally, identical lighting and photography circumstances are maintained. Figure 1 displays the 10 groups of pictures of both healthy and unhealthy leaves.

Preprocessing

There are input image size requirements for the different CNN networks (both for studies in segmenting and classifying). In order to accommodate the different U-net segmentation network variants, the images are therefore scaled to 256x256. Similar to this, the images are scaled to 299x299 before being used to train the Inception ResNet V2 model.

Augmentation

Due to the imbalance in the dataset and the lack of a comparable proportion of images for each group, training using an imbalanced set of images can produce an unreliable model. Data augmentation is therefore crucial for preparing the data in order to increase the number of pictures and decrease excess fitting. The training images are balanced using a variety of data augmentation techniques, including flip, rotation, and zoom. This flipping process creates a flipped image that is equal to the original in both the vertical and horizontal directions. Each time the rotation procedure is used, a new image is created that has been slightly rotated at a random angle of up to 90 degrees. Every image is randomly zoomed by up to 20% in Zoom.

The size and composition of a dataset affect the ratio of its training, validation, and test groups in deep learning. In a typical split ratio, ninety percent of the data is typically utilized for training as well as validation, and ten percent is utilized for testing. 90% of the data used were split into 10% for validation and 80% for training. A training dataset is the group of data that is employed to train a CNN. The framework is trained on a substantial amount of data with labels, which is then used to train the model to make predictions on new, inactive data in addition to improve the model's accuracy in making predictions. A gathering of data called a validation dataset is used to assess how well a CNN performed throughout training. The algorithm's generalizability to new, untested data is assessed using a validation dataset. Compared to the validation dataset, the training dataset is bigger. Instead of just memorizing the training data collection, the model may be trained to improve its ability to perform on fresh data using a validation dataset. A dataset used to assess a CNN after training is known as a testing dataset. The testing database, which is different from each of the validation and training data sets, is utilized to gauge how well the framework performs when applied to new, untested data. The testing database offers an unbiased assessment of the model's success. It is employed to assess how well different models or variations of the same model perform.

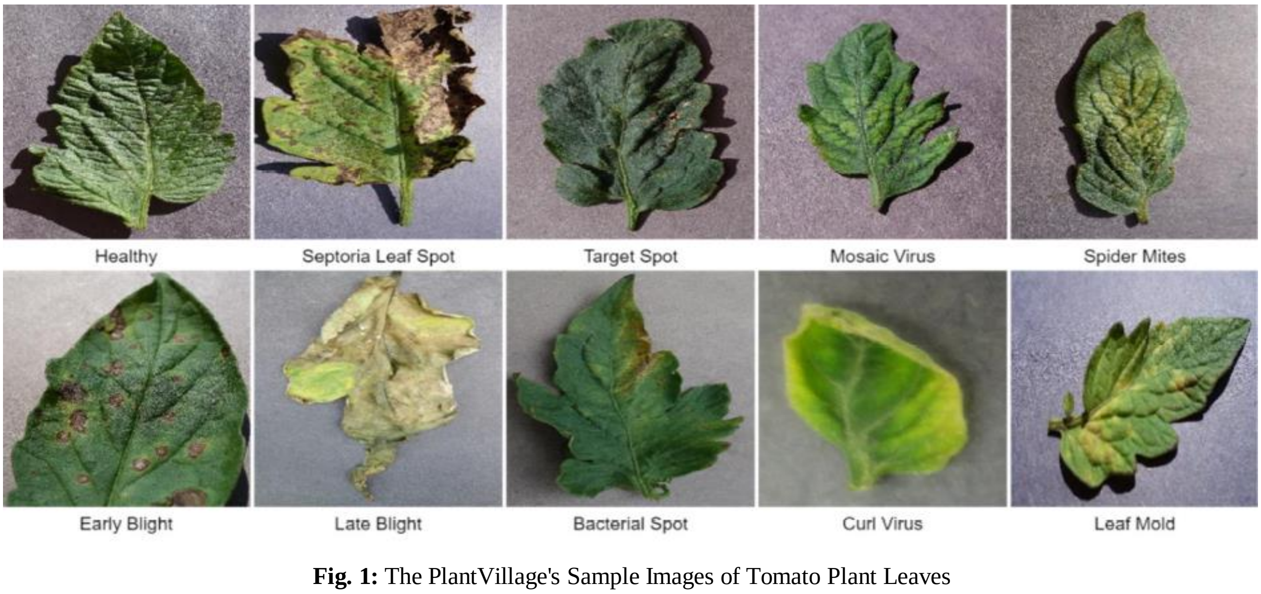

Fig. 1: The PlantVillage's Sample Images of Tomato Plant Leaves

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Hybrid AI Model for Tomato Crop Disease

Deep learning has enabled major advancements in image classification. As discussed in the related work section, CNN along with numerous additional architectures have currently been attempted and evaluated with a variety of outcomes. The quickest and most straightforward method for improving the performance of these types of systems is to increase the scale of a deep neural network. Here, we propose a novel hybrid design that fuses various methodologies. The method is divided into three major components: segmentation, CNN modeling, and SVM classifier. Figure 2 illustrates its design.

Segmentation Phase: Modified Unet

U-Net is an advanced deep learning-based image segmentation framework. It was developed with the intention of segmenting biological images. The U-shaped network design is referred to as a "U-net". U-net, in contrast to conventional CNN models, uses convolutional layers to upgrades or reassembles mappings of featuresinto an entire picture. In the literature, there are many segmentation algorithms built on U-nets. In this study, a modified U-Net is examined to determine which one performs the best. Figure 3 depicts the Modified U-Net's construction.

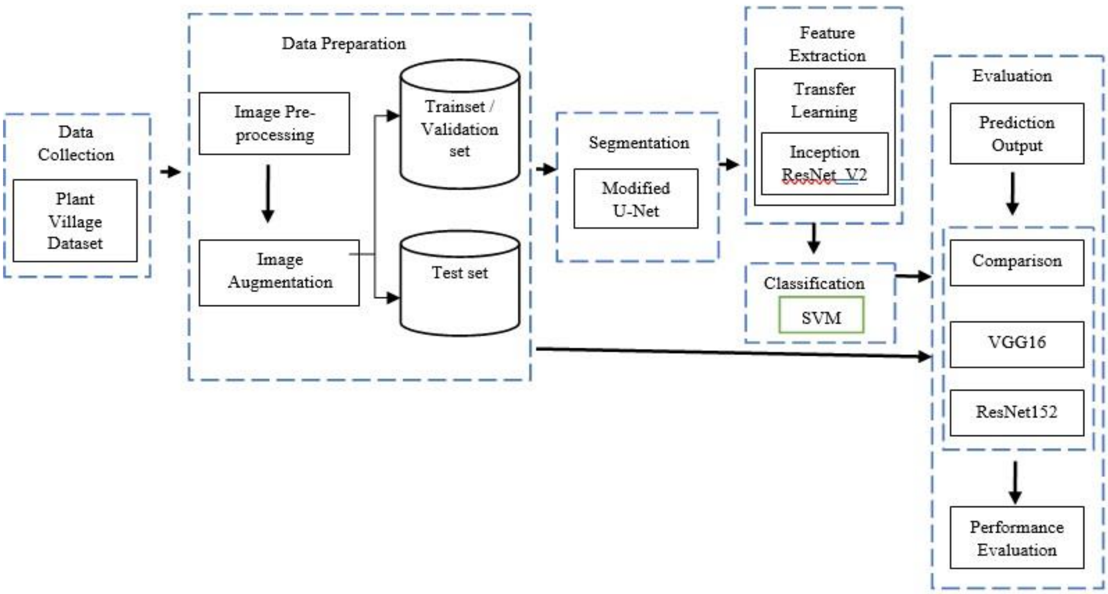

Fig. 2: Proposed Architecture Design

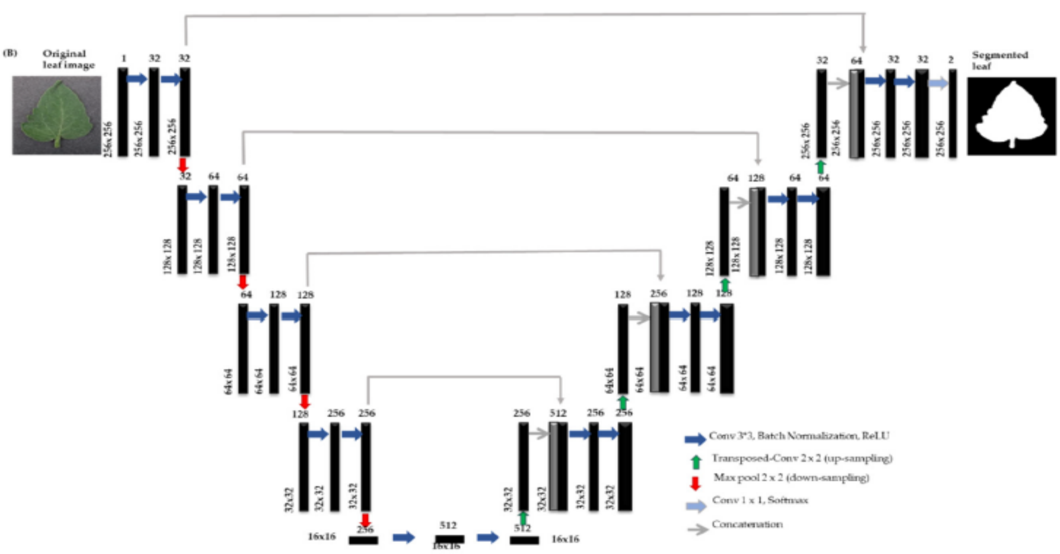

Fig. 3: Architecture of Modified UNet

Utilized is the Modified U-Net, a variant of the U-Net architecture that differs slightly in its decoding portion. In the original base model, a route that contracts and has four encoding units is succeeded by a path that expands and has four decoding units. Each encoding block is composed of two consecutive 3x3 convolutional layers. A down sampling max pooling layer with a stride of 2 follows. The decoding blocks consist of two 3x3 convolutional layers, one of which is convolutional that has been upsampled and transposed, in addition to the matching feature map through the contracting route. In the modified U-Net architecture, the decoding block has three convolutional layers instead of two. The updated decoder consists of an upsampling layer, two 3x3 layers of convolution, the concatenation layer, along with one last 3x3 convolutional layer. The batch normalization along with ReLU activation are applied to the expansion of all convolutional layers. Every pixel is mapped onto a binary class of background at the final layer using a pixel-by-pixel SoftMax. The output from the ultimate decoding block is then mapped using 1x1 convolution to two channel feature maps.

Feature Extraction Phase: Inception ResNet V2

The feature generator in the suggested approach was based on the previously trained design Inception ResNet V2. The strategy is to extract features from these trained designs without using their ultimate classification layer, and then to feed those features into shallow classifiers. To improve accuracy without overtaxing computer resources, inception starts by estimating a sparse structure, enlarging its depth and breadth, and clustering scant data into a dense structure. GoogLeNet (Inception) and ResNet are combined in the Inception ResNet V2 design. To establish a direct connection with the structure defined as the highway network notion is the core idea behind ResNet.The highway network allows for the retention of a portion of the outcomes from the previous network layer, despite the fact that its layout represented a non-linear adaptation of the functionality input. It allows the subsequent layer to receive the initial incoming data right away. ResNet, on the other hand, can guarantee data integrity by sending information straight from input to output. 132 convolutional layers, 5 pooling layers, and a dense layer make up Inception ResNet V2.

The dropout procedure in CNNs can lead to overfitting issues because of their numerous parameters. Dropout is a technique for randomly detaching that has a 1-p dropout probability and may separate connections between various nodes. The dropout layer decreases the total amount of model factors while enhancing algorithm resilience. The stochastic inactivation layer strengthens the network structure and helps the model prevent overfitting. Recently, deep neural network overfitting was significantly reduced using dropout. Dropout randomly stops only a certain amount of neurons in each of the layers during each epoch, using the remaining neurons for forward as well as backward propagations.Because of this, the functioning neurons are more resilient and motivated to do so because they can extract helpful features far more efficiently and independently lacking the assistance of the neurons that are inactive.As a consequence, the network as a whole has greater generalization capacity while the joint adaptability of neurons is decreased.

Classification Phase: Support Vector Machine (SVM)

A support vector machine is a supervised ML technique for outlier identity, regression, and classification. However, classification problems are its main use. A collection of training data is mapped into a space with high dimensions using SVM, and the most suitable hyperplane or a group of hyperplanes that divides the data elements into prospective subclasses is then constructed. The input data can be changed to the necessary shape by utilizing SVM kernel functions. The SVM uses a variety of kernels. The linear kernel was used in this study because it outperformed the others in terms of efficiency. The linear kernel can be optimized more quickly and with fewer factors (only the C regularization parameter). The following can be expressed as the linear kernel:

$$\mathscr{k}(x_a, x_b) = x_a * x_b \tag{1}$$

Where x_a, x_b denote the input features.

By increasing the margin about the support vectors to the hyperplane, the greatest distance across data points can be achieved. To find the maximum margin, the SVMs try to answer the subsequent optimal problem:

$$min_{\omega,\rho,\zeta} \frac{1}{2} w^T w + C \sum_{a=1}^{n} \zeta_a \tag{2}$$

$$y_a(w^T \phi(x_a) + \rho) \geq 1 - \zeta_a \tag{3}$$

Where ζ indicates separation from the proper margin with $\zeta \geq 0$.

i = 1,.., n
C indicates a regularization constant
$w^1 w = \|w^2\|$ indicates the normal vector
$\phi(x_a)$ indicates the transformed input vector
ρ stands for a bias measure
y_a indicates the i_{th}target value

Additionally, SVM has been used frequently in situations involving image classification and has attained effective classification accuracy. In the suggested model, an SVM classifier was used instead of the multilayer perceptron outcome from the CNN model.

Results and Discussion

To compare performance in the proposed study, we also used some pre-trained models. Following is a brief overview of these pre-trained models.

VGG16

Powerful and precise classification abilities are provided by the VGG. It was created by the Visual Geometry Group as part of the CNN concept for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (VGG). The input image size for this design is 224x224. Padding is used to maintain the same resolution of the intermediary outputs and filters are 3x3 in size. It has 3 Deep layers and 13 Convolution layers. ReLU is used as the activation function in all levels. The 1000 output nodes in the final level, which corresponds to the ILSVRC's 1000 classes, and the 4096 hidden nodes in each of both the penultimate levels make up the final layer's structure. It was tried to load the VGG16 pretrained weights, and an outcome layer with ten parameters corresponding to ten categories of tomatoes was also added. It found that transfer learning with VGG16 didn't turn out very encouraging in the collection of tomato leaves that was constructed using the Plant Village data sources files.

Residual Network (ResNet)

This was first launched in 2015, and with an error rate of 3.57%, it also took first place in the ILSVRC competition. ResNet's high accuracy rate is primarily due to the addition of residual layers, which enable a deeper network design than was previously possible with popular network designs (20). The diminishing gradient problem is alleviated when programming a deep network where the previous layer is passed to the subsequent layers by the remainder of the layer, which is also referred to as identity mapping. The goal was to get around the initial learning feature's reduction of input features, which results in zero features.

The NVIDIA DGX v100 machine has been used to run the suggested hybrid CNN model. The primary libraries used for the hybrid AI model's implementation were Python 3, a Keras pack, and Matplotlib. The default settings of the parameters used for training were selected to enable the framework to effectively extrapolate new data and to generate precise projections using test data. For all the models using CNN, the initial learning measure was specified as 0.0001 and the Adam optimizer's epoch was put at 30. Adam is a well-known optimization method. It is a development of the widely used optimization technique known as gradient descent that is employed in the training of DL models. One of the factors it is such a popular choice is because it is also computationally efficient; identification jobs have frequently been finished with its assistance.

The primary goals of the suggested design included lowering incorrect categories and increasing tomato leaf identification accuracy. The created hybrid model's effectiveness was assessed using the metrics accuracy, precision, recall, and F1-score (Eqs. 4–7):

$$Accuracy = \frac{t_p+t_n}{t_p+f_p+t_n+f_n} \times 100\% \quad (6)$$

$$Precision = \frac{t_p}{t_p+f_p} \times 100\% \quad (5)$$

$$Recall = \frac{t_p}{t_p+f_n} \times 100\% \quad (6)$$

True positive (t_p) is the proportion of accurately categorized images of healthy leaves, and true negative (t_n) is the proportion of accurately categorized images of unhealthy leaves. False positive (f_p) and false negative (f_n) are terms used to describe the wrongly labeled both healthy and unhealthy leaf visuals, respectively.

Different tests were run on segmented images of tomato leaves in this research. Table 1 compares the results of Four pretrained CNN (such as AlexNet, VGG16, ResNet152, and InceptionResNet V2) when used in a machine learning classification strategy for segmented leaf images. According to identical experimental circumstances as the other models (ResNet152 and VGG16), the proposed hybrid AI model in this study demonstrated remarkable average testing accuracy of about 97.87%.

Accuracy Analysis

Here four models namely AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2is used to evaluate the leaf disease dataset. Table 1 and Figure 4 represent Accuracy obtained by AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2. The results obtained clearly proves that proposed InceptionResNet V2average Accuracy is 97.87%, ResNet152 Accuracy is 95.08%, VGG16 Accuracy is 93.4% and AlexNet Accuracy is 91.6% respectively. From the result it's proved that proposed InceptionResNet V2performs better than other existing algorithms in terms of Accuracy.

Table 1: Accuracy Comparison

Algorithms	Accuracy %
AlexNet	91.6
VGG16	93.4
ResNet152	95.08
InceptionResNet V2	97.87

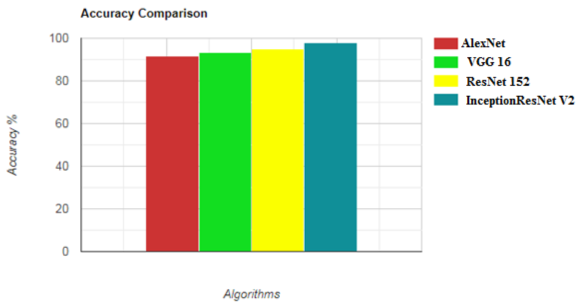

Fig. 4: Accuracy Comparison Graph

Precision Analysis

Here four models namely AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2is used to evaluate the leaf disease dataset. Table 2 and Figure 5 represent Precision obtained by AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2. The results obtained clearly proves that proposed InceptionResNet V2average Precision is 0.96, ResNet152 Precision is 0.93, VGG16 Precision is 0.93 and AlexNet Precision is 0.90 respectively. From the result it's proved that proposed InceptionResNet V2performs better than other existing algorithms in terms of Precision.

Recall Analysis

Here four models namely AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2is used to evaluate the leaf disease dataset. Table 3 and Figure 6 represent Recall obtained by AlexNet, VGG16, ResNet152 and proposed InceptionResNet V2. The results obtained clearly proves that proposed InceptionResNet V2average Recall is 0.94, ResNet152Recall is 0.92, VGG16Recall is 0.90 and AlexNetRecall is 0.89 respectively. From the result it's proved that proposed InceptionResNet V2performs better than other existing algorithms in terms of Recall.

Systems for detecting diseases using computer vision are well-liked because of their dependability, simplicity in data collection, and speed of findings. The effectiveness of scaling models in CNN-based frameworks is compared in this research when it comes to tasks like the process of segmentation, extraction of features and classification of images of tomato leaves. Despite the fact that various diseases have symptoms that are similar, resulting in low-class variance, the suggested hybrid model seemed to be capable of separating the data with high accuracy. We experimented with various CNN architectures, including VGG16, ResNet152, and InceptionResNet V2, but due to its superior accuracy, a hybrid CNN model incorporating InceptionResNet V2 was chosen as the basis for the proposed model.

The majority of the tomato plant images' identified categories, as seen in Figure 4, corresponded to the real types of the plants. For example, a "bacterial spot" was correctly identified as the disease present in Figure 4 with a probability of higher than 99.30%. The suggested technique also successfully identified each sample in Figure 7. The findings support the hypothesis that the presented hybrid network helps to increase the accuracy of tomato leaf detection.

Table 2: Precision comparison

Algorithms	Precision
AlexNet	0.90
VGG16	0.93
ResNet152	0.93
InceptionResNet V2	0.96

Table 3: Recall Comparison

Algorithms	Recall
AlexNet	0.89
VGG16	0.90
ResNet152	0.92
InceptionResNet V2	0.94

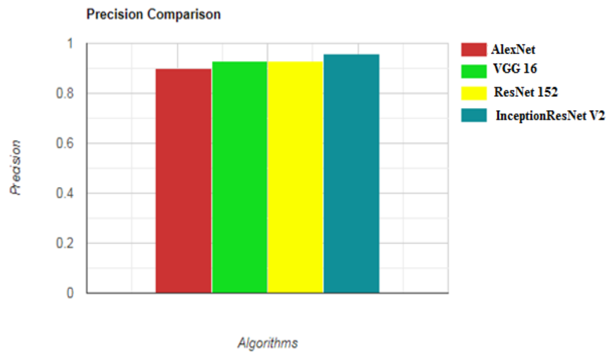

Fig. 5: Precision comparison graph

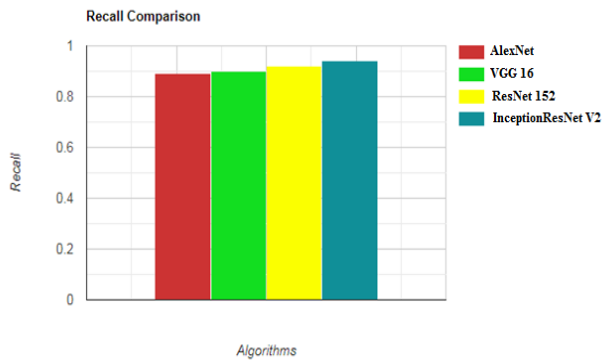

Fig. 6: Recall comparison graph

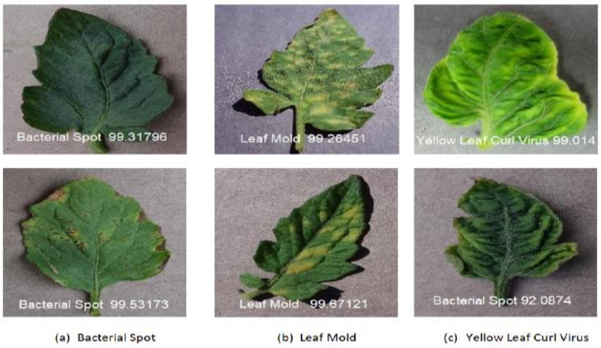

Fig. 7: The test data samples of tomato plant disease identification findings

Conclusion

This study set out to develop a hybrid AI framework as a diagnostic technique for classifying nine distinct crop diseases in tomato leaves. Three primary subsystems U-Net, CNN, and SVM with transfer learning form the basis of this hybrid categorization model. This hybrid diagnostic tool displayed with 97.87% accuracy, 0.96 precision and 0.94 recall. The obtained findings demonstrate that the model, which makes use of the most well-liked publicly accessible Plant Village dataset, outperforms a few recent deep learning techniques. The advantages of this system include its quick working speed, lack of unnecessary epochs and criteria, as well as early discovery. These advantages make it possible for this technology to work in an environment that is constantly changing. In the modern era, drones are used to photograph the underlying crops or woods in order to build a precise and compact dataset. The proposed system's quicker processing speed makes it a prime candidate for drone installation to enable real-time crop disease detection. In the future, we will research and employ innovative transfer learning techniques with multi-layer feature extraction on pre-trained models in order to select the most effective layers that offer the most outstanding features.

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Authors Contributions

P. Loganathan: Planning, Design concepts and Data collection.

M. John Britto: Coding, Implementation and Algorithms.

Vinston Raja: Overall execution, Results comparison and Publication.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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