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A Comparative Study of Convolutional Neural Network Architectures for Enhanced Tomato Leaf Disease Classification Using Refined Statistical Features

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ABSTRACT

Tomatoes, a staple in culinary practices, are currently in high demand yet low supply in India, rendering them unaffordable to the general population. This issue largely stems from the inability of farmers to identify and control prevalent tomato leaf diseases, leading to significant crop losses. Early detection and classification of leaf diseases are paramount to mitigate this problem, thereby boosting crop productivity. Despite extensive research in this domain, the precise localization and identification of various tomato leaf diseases present a complex task. This complexity arises from the significant overlap between the healthy and diseased portions of the leaves. The process is further complicated by the minimal contrast between the background and foreground of the specimen under investigation. To address these challenges, this study conducts a comprehensive performance analysis of several Convolutional Neural Networks (CNNs) models, namely, ResNet-152, ResNet-101, VGGNet, Alex Net, and LeNet, applied to the PlantVillage dataset. The results indicate that the ResNet-152 and ResNet-101 models yield superior accuracy rates when applied to both full-resolution source images and their background-removed counterparts. The performance outcomes reported herein surpass those documented in the existing literature, demonstrating the potential for significant advancements in the early detection and classification of tomato leaf diseases.

1. INTRODUCTION

Vegetable cultivation is an essential facet of India's agricultural sector, with a multitude of factors influencing its yield [1]. Over the past few decades, India has seen substantial growth in vegetable production [2], positioning itself as a significant contributor to the global vegetable market, second only to China. As a cornerstone of the Indian economy [3], agriculture faces considerable challenges due to plant diseases, which, if unaddressed, can drastically reduce output [4].

Tomatoes are among the most consumed vegetables in India. However, every part of the tomato plant is susceptible to disease, with even minor phonological alterations in the leaves potentially leading to abnormal growth, discoloration, damage, and ultimately plant death [5]. Therefore, regular inspection of plants for pests, rodents, and other environmental threats is imperative [6]. Apart from insects, factors such as bacteria, viruses, fungi, and improper farming practices can also contribute to tomato diseases.

These diseases encompass bacterial spots, leaf mold, Septoria leaf spots, early blight, mosaic virus, late blight, yellow curl virus, and target spot spider mites. With advancements in technology, the identification of plant leaf diseases can now be automated using computer vision, image processing, and deep learning techniques, as opposed to manual identification, which is prone to human error.

Deep learning (DL) techniques have seen widespread use in the agriculture industry over the past two decades. Convolutional neural networks (CNN), a popular deep learning method, have shown promise in accurately categorizing diseases [7, 8]. Other alternative models such as ResNet-152, ResNet-101, GoogleNet, VGGNet, and LeNet have also been explored.

Deep learning has emerged as the benchmark for diagnosis of tomato plant diseases. It enables the sorting of infected leaves and the pixelization of annotated images, providing additional data for analysis. Deep learning models, especially CNNs, are able to perform automatic feature extraction, which helps in image classification. Post feature extraction, the most informative features are selected for classification.

CNNs are widely adopted for deep learning identification due to their inherent learning abilities, making them ideal for feature extraction and image categorization. The applications of CNNs span various domains including author recognition, object detection, and image text detection. CNNs learn feature extraction and categorization to better comprehend images, which has enabled advancements in text detection in sceneries, biological image analysis, and facial recognition.

CNNs leverage global regional background information to infer more robust features and can correct for shadows, distortions, and brightness oscillations in natural photographs through image processing. The sensitivity of CNN algorithms to key features makes them particularly effective in plant leaf image analysis and leaf disease analysis. Their ability to utilize a larger dataset has led to significant successes in plant disease identification.

In this study, we evaluate and compare the performance of several convolutional neural network (CNN) models on the PlantVillage dataset. The evaluation metrics include image restoration and segmentation, accuracy, and other metrics used during the training, validation, and testing phases. Upon analysis, we found that, among all the models, ResNet-152 demonstrated superior performance across all metrics.

2. IMAGE PRE-PROCESSING STEPS

To improve the quality of images and extract useful data for analysis, image pre-processing is a crucial stage in the disease detection process for tomato plant leaves. Pre-processing images in order to spot diseases on tomato plant leaves involves several steps as shown in Figure 1 Standardization and normalizing ensure image comparability. These methods standardize image scale, range, and color space for fair and meaningful comparisons. Standardization reduces illumination, camera, and image capture variances, making diseases classification algorithms more robust. Preprocessing approaches prepare images for feature extraction. Features like color histograms, texture descriptors, and form parameters are extracted from sick patches. Extracting discriminative characteristics helps classify damaged tomato leaves more accurately. Preprocessing pipeline data augmentation can enhance dataset diversity and size. Data augmentation boosts diseases classification model resilience and generalization by adding samples with different illumination, rotations, flips, or noise levels. Image preprocessing improves image quality, reduces noise, segments significant sections, and extracts useful characteristics. The preprocessing pipeline improves tomato plant leaf disease classification by improving data quality and relevance. It allows machine learning or deep learning models discover the patterns and correlations between image data and disease classes, enabling tomato disease control.

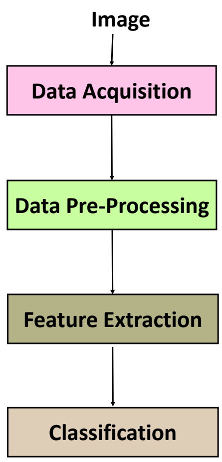

Figure 1. Pre-processing steps for image diseases classification

Data Acquisition: The dataset is made up of a set of different image classes and several images. These numbers were taken from the primary dataset that was collected from PlantVillage, ten classifications and 14529 images of tomato leaf diseases are included in the data collection. They are check leaves, stems, and fruits for discoloration, stains, wilting, and abnormalities. They document and image afflicted plants with notebooks, cameras, or phones. Tomato plant leaves are captured with digital cameras or sophisticated equipment. To see the leaves, several images are taken from different perspectives. Disease signs are highlighted in the images. Experts carefully outline impacted leaf parts. This stage helps deep learning models identify disease trends.

The tests' findings diseases, severity, and other findings are recorded. This data trains and validates disease detection models. The dataset includes field observations, annotated images, and laboratory test findings. This dataset shows tomato plant diseases visually and diagnostically. Data integration connects sources for analysis. Images, annotations, and lab results are organized. Depending on project size and needs, it can be stored in a database, file system, or cloud. Data organization and documentation improves management and retrieval. Rotating, flipping, resizing, and adding noise to images creates more diversified and larger datasets. Data augmentation exposes deep learning models to more disease variants, improving their reliability and generalizability. Pre-processed data is used to identify features, train models, and predict diseases. Using gathered data, deep learning algorithms automatically detect and classify tomato plant diseases based on visual signs. Disease detection models depend on data quality and representation.

Pre-Processing: This is done in order to change the data into a form that can be used by the feature extraction approach as well as the stages that come after it. During this step, augmentation and normalization of the data are carried out.

Feature Extraction: First, the important features are retrieved so that we may answer the categorization problem that we have. Color, form, and texture are all characteristics of an image. The texture feature is given a greater amount of attention by diagnostic algorithms that use photos of leaves to identify disorders.

Feature extraction for tomato disease identification uses data such as tomato leaf images to represent healthy and diseased plants. This describes tomato disease detection feature extraction. Image pre-processing improves image quality and standardization before feature extraction. Resizing, color normalization, noise reduction, segmentation, and other techniques from image pre-processing may be used. First, select tomato leaf areas of interest (ROIs) if the image has many leaves. Image segmentation or leaf boundary delineation can do this next, identify tomato leaf disease symptoms in each ROI. Image processing algorithms like deep learning can segment diseases spots, lesions, discoloration, and other apparent indicators of disease. Localized symptoms of disease can be analyzed using feature extraction approaches. Common tomato disease detection feature extraction methods include:

a. Colour Features: Color histograms, color moments, and color channel statistics can show color differences between healthy and unhealthy regions.

b. Texture-based Features: Use Gabor filters, LBP, or GLCM statistics to define healthy and diseased areas' texture patterns.

c. Shape-based Features: Calculate disease symptoms' geometric features such area, perimeter, circularity, and aspect ratio.

d. Statistical Features: Extract mean, standard deviation, skewness, and kurtosis from disease symptom pixel intensities to record their statistical distributions.

e. Deep Learning Features: Use VGG, ResNet, or Inception pre-trained CNNs to extract high-level features from localized illness symptoms. Feature vectors are CNN intermediate layers.

Depending on the collected features' dimensionality and modelling needs, feature selection or reduced dimensionality may reduce feature space complexity. This eliminates unnecessary data and improves model efficiency and generalization. Numerical feature vectors represent extracted features. Each tomato leaf ROI has traits that describe its disease symptoms. Machine learning or deep learning models are trained using extracted feature vectors and their labels signifying health or sickness. These models discover diseases class patterns using extracted features. Based on extracted attributes, trained algorithms may forecast disease in new tomato leaf samples. Feature extraction from tomato leaf images distinguishes healthy and sick plants. It allows the creation of precise and reliable disease detection models for tomato agriculture disease control.

Classification: Image classification refers to the process of determining what something depicted in an image symbolizes. It is possible to train a model to recognize different kinds of images through the use of a categorization model. You may train a model, for instance, to recognize photographs depicting three distinct species of leaves.

The image pre-processing methods that have been described so far can be used to carry out the same procedure on tomato leaf leaves and categorize them in accordance with their traits.

3. TOMATO LEAF DISEASE CLASSIFICATION

Both biotic (life-related) and abiotic (environmental) elements, such as rain, spring frosts, weather patterns, chemical burning, etc., can cause plant diseases. Less hazardous and avoidable diseases are those that are not infectious and transmittable. Biological diseases are the main source of agricultural damage. The three primary kinds of disorders are shown in Figure 2.

Fungal Diseases: fungus or organisms that resemble fungus account for over 85% of plant diseases. Fungus spores are tiny and light, making it simple for them to travel to nearby plants or trees. Fungal diseases can impair tomato productivity, quality, and health. Fungal diseases in tomato plants: symptoms, causes, and effects. Tomato plant fungal diseases include Leaf Spots, Fruit Rot, Stem Cankers, Powdery Mildew, Damping-Off, and its symptoms. Pathogen presence, favorable environmental conditions, plant stress, and disease spread cause tomato plant fungal diseases, which reduce yield, quality, plant death, and disease spread.

Early detection, fast intervention, and a holistic disease management approach are essential for tomato plant health and fungal disease mitigation.

Leaf Mold: The main causes of this fungus disease are wet leaves and high humidity. One of the indications is yellowing of leaf surfaces [9, 10]. Tomato plants often suffer from Fulvia fulva (previously Cladosporium fulvum) leaf mold. Leaf Mold on tomato plants symptoms, causes, and effects. Leaf Mold causes leaf lesions, fuzzy growth, yellowing, leaf drop, and reduced photosynthesis in tomato plants. Fungal pathogens, humidity, overcrowding, and poor air circulation cause tomato leaf mold. Reduced Photosynthetic Capacity, Premature Defoliation, Yield Loss, Disease Spread, Remove and Destroy Infected Leaves.

Early blight: It is brought on by fungus or bacteria. Initially, older leaves get black spots. The stem may get attached to or lose dead, dry leaves from diseased leaves [7, 8]. Early Blight, which is caused by the fungus Alternaria solani, is one of numerous diseases that affect tomatoes. Symptoms, causes, and consequences of early blight. On tomato plants, early blight enlarges the leaves, stems, fruits, and lesions. Fungal pathogens, warm and humid conditions, plant stress, and overcrowding cause early tomato blight. Early Blight reduces tomato plant leaf photosynthesis, defoliation, yield loss, and disease spread. Preventive methods and prompt management can reduce Early Blight's impact on tomato plants, enhancing output and quality.

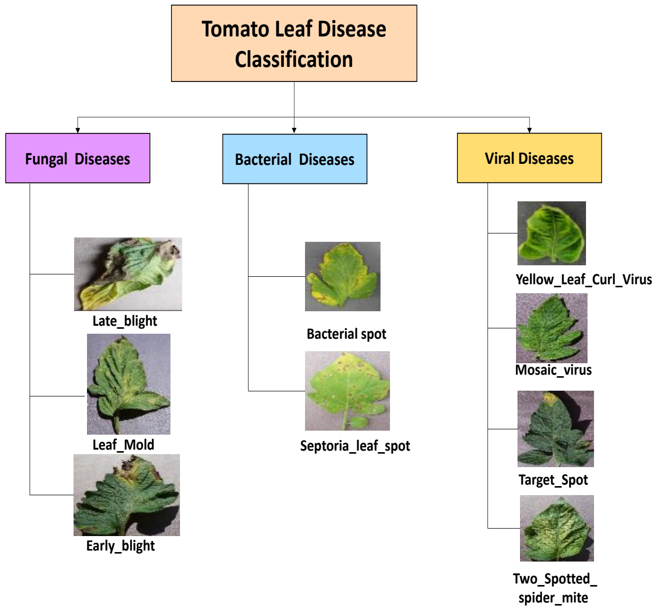

Figure 2. Tomato leaf diseases classification

Late blight: Diseases brought on by a fungi disease. The late blight first manifests itself on leaves [9, 10]. Late Blight, caused by Phytophthora infesting, can devastate tomato plants. Late Blight in tomatoes: symptoms, causes, and effects. Late Blight in tomatoes causes leaf lesions, lesion spreading, stem lesions, white fungal growth, fruit lesions, and Late Blight in tomato plants is caused by fungal pathogens, favorable environmental conditions, host susceptibility, and rapid disease progression, yield loss, defoliation, plant decline, and disease spread.

Late Blight can damage tomato plants if not treated quickly and thoroughly. Early detection, prevention, and cultural interventions can preserve tomato crops from this deadly disease.

Bacterial Diseases: There are about 200 different types of bacteria responsible. Insects, water splashes, infected tools or plants, and wind can all spread the disease. Bacterial infections impair tomato productivity, quality, and health. Bacterial infections in tomato plants: symptoms, causes, and effects. Bacterial Diseases in Tomato Plants Caused by Bacterial Pathogens, Warm and Moist Conditions, Infected Plant Material, and Yield Reduction, Fruit Quality Decline, Plant Decline and Death, Disease Spread.

Bacterial diseases on tomato plants must be detected early, treated quickly, and managed holistically. Preventive strategies, cultural practices, and tailored therapies can protect tomato crops from bacterial infections.

Bacterial_spot: The disease is caused by Xanthomonas species. Crops are compelled to shed their leaves due to the extreme temperatures and windy circumstances [9, 10]. Bacterial Spot, caused by Xanthomonas campestris is a frequent and severe tomato plant disease. Bacterial Spot in tomatoes: symptoms, causes, and effects. Bacterial Spot in Tomatoes causes Leaf Spots, Spot Enlargement, Leaf Blighting, Stem and Fruit Lesions, and Bacterial pathogens, warm, humid conditions, splashing water, and plant contact cause tomato plant bacterial spot. Bacterial Spot-on Tomato Plants Reduce Yield, Fruit Quality, Plant Decline and Defoliation, and Disease Spread.

Bacterial Spot-on tomato plants must be detected early, treated quickly, and managed holistically. Preventive, cultural, and targeted treatments can protect tomato crops from this deadly disease.

Septoria Leaf spot: It's connected to fungal. On the lower leaves, the first fruit develops. Each leaf has a number of rounds of dark-brown spots [9, 10]. Septoria Leaf Spot, caused by the fungus Septoria Lycopersicon, is a frequent tomato foliar disease. Septoria Leaf Spot in tomatoes: symptoms, causes, and effects. Septoria Leaf Spot in Tomato Plants causes Fungal Pathogen, Splashing Water and Humidity, Residue in Soil, Reduced Photosynthetic Capacity, Defoliation, Yield Loss, and Disease Spread.

Septoria Leaf Spot can be minimized on tomato plants via early detection, quick response, and integrated disease control. Preventive, cultural, and targeted therapies can protect tomato crops from this foliar disease.

Viral Diseases: Viral infection is the source of one of the strangest plant diseases. Because a virus cannot be treated chemically once it has infected a plant, it is necessary to destroy all suspect plants in order to stop the infection. Due to their requirement to physically enter the plant, insects are the most common vectors of these diseases.

Viral infections can impair tomato productivity, quality, and health. This overview covers tomato plant viral infections' symptoms, causes, and effects. Tomato plant viral diseases cause mosaic patterns, leaf curling and deformation, stunted growth, reduced fruit quality, and fruit drop. and Vector Transmission, Infected Plant Material, Grafting Cause Tomato Plant Viral Diseases, which Reduce Yield, Fruit Quality, Plant Decline, and Disease Spread.

There is no prevent for plant viral infections, but preventive measures and cultural practices can help tomato plants grow healthier. Managing viral infections requires early discovery, prompt action, and sound agricultural practices.

Yellow leaf curl: This tropical and subtropical diseases results in monetary losses. Whiteflies are the carrier of it. This disease's symptoms include upward cupping or curling, decreased leaves, and stunting [9, 10]. Tomato plants are infected by the tomato yellow leaf curl virus (TYLCV) and other viruses. Tomato yellow leaf curl: signs, origins, and consequences. Leaf curling, yellowing, thickness, stunted development, and decreased fruit yield and quality are all signs of yellow leaf curl in tomato plants. Insect transmission and viral infections are some of the causes. Preventive methods and cultural practices can help tomato plants cope with Yellow Leaf Curl and develop healthier. Managing Yellow Leaf Curl requires early discovery, prompt action, and appropriate farming practices.

Mosaic Virus: The tomato mosaic virus, which yellows and stunts plants, is to blame for crop loss. Curled, distorted, or undersized leaves are symptoms [9, 10]. Mosaic viruses like ToMV and TMV can infect tomato plants. Mosaic Virus in tomato plants: symptoms, causes, and effects. Mosaic Virus in Tomato Plants Causes are Viral Pathogens, Mechanical Transmission, Reservoir Hosts, and Impacts are Yield Reduction, Fruit Quality Decline, Plant Decline, and Disease Spread.

Preventive measures and cultural practices can help tomato plants resist Mosaic Virus and generate healthier crops. Mosaic Virus management requires early discovery, prompt response, and sound agricultural practices.

Target spot: Tomato growth is best at 68 to 82°F temperatures and 16-hour leaf wetness intervals. The end effect is concentrated leaf necrosis [9, 10]. Target Spot can severely damage tomato plants. Target Spot on tomato plants symptoms, causes, and effects. Target Spot in Tomato Plants causes Leaf Lesions, Lesion Enlargement, Leaf Blighting, Stem Lesions, Fruit Lesions, and Target Spot causes reduced leaf photosynthesis, defoliation, yield loss, and disease spread in tomato plants.

Preventive and timely care can reduce Target Spot's influence on tomato plants, enhancing output and fruit quality.

Two-spotted spider mite: Spider insects are the source of tomato leaf spots. After a few days of mite feeding, the leaves become yellow or grey and fall [9, 10]. Tetranychus urticae, a two-spotted spider mite, can affect common tomato plants. Symptoms, causes, and effects of the two-spotted spider mite on tomato plants. A two-spotted spider mite infestation on tomatoes causes leaf damage, webbing, decreased plant vigor, early leaf drop, warm, dry weather, the absence of natural predators, environmental stress, and other symptoms. Reduces Photosynthesis, Fruit Damage, Plant Stress and Decline, and Disease Transmission in Tomato Plants due to Two-Spotted Spider Mite Infestation.

These management measures reduce Two-Spotted Spider Mite damage to tomato plants, preserving plant health, yield, and fruit quality. Control requires early detection and proactive pest treatment.

Ten different forms of diseases, including the Leaf Curl Virus, Late Blight, Leaf Mold, Early Blight, Mosaic virus, Target Spot, Septoria Leaf Spot, Yellow Leaf Curl Virus, Spider Mites, Bacterial Spot, and Healthy Class, can infect the leaves of tomato plants.

CNN architectures can classify tomato leaf diseases from input images. Here's their operation and differences. Deep CNNs ResNet-152 and ResNet-101 can extract complicated tomato leaf characteristics. Their deeper structures capture disease patterns and features. These structures suit datasets with several diseases and complex leaf symptoms. Their depth may need more processing resources and training time than other architectures. VGGNet has uniform architecture with modest 3x3 convolutional filters and max pooling layers. Hierarchical representations of incoming images—including diseases patterns—are learned. VGGNet is computationally intensive but accurate. It works well for datasets with many clinical symptoms and fine-grained feature extraction. Inception modules in GoogleNet capture features at different scales using numerous filter sizes (1×1, 3×3, 5×5). These modules' parallel convolutions capture different and multi-scale disease-related characteristics. For large datasets and real-time applications, GoogleNet is accurate and computationally efficient. It can classify images and treat many diseases. LeNet is a shallow early CNN architecture. Convolutional and pooling layers precede fully linked layers. For basic disease identification applications, LeNet can still perform well.

It works well with little computational resources. These architectures differ in depth, network structure, and feature extraction difficulty. ResNet-152 and ResNet-101 can detect more complex illness patterns, while VGGNet and GoogleNet balance accuracy and processing efficiency. LeNet, however superficial, can detect minor diseases. The dataset complexity, computational resources, and tomato leaf disease detection accuracy-efficiency trade-off determine the architecture.

ResNet-152 is the most layered architecture, followed by ResNet-101. VGGNet has fewer layers than ResNet models yet a deep structure. ResNet and VGGNet are deeper than GoogleNet and LeNet. Deeper architectures mean more parameters for ResNet-152 and ResNet-101. VGGNet, especially VGG16 and VGG19, contains several settings. Inception modules help GoogleNet use less parameters than the above designs. LeNet, an earlier and simpler architecture, has fewer parameters than the other variants. Computational Complexity Due to greater layers and parameters, ResNet-152 and ResNet-101 are computationally more demanding.

VGGNet's many parameters, especially in deeper variants, make it computationally costly. GoogleNet is less computationally intensive than ResNet and VGGNet because it balances accuracy and efficiency. LeNet's shallow architecture requires less computing. ResNet-152, ResNet-101, and VGGNet can improve accuracy, especially on complicated datasets. GoogleNet is accurate and efficient in image classification. LeNet, however shallow, can perform simple classification jobs well. These statistical discrepancies affect model performance, training, and inference computational resources. When choosing a CNN architecture for tomato leaf disease classification, consider resources, dataset complexity, and accuracy vs. computational efficiency.

4. DEEP LEARNING TECHNIQUES FOR LEAVES DISEASE DETECTION

Deep learning algorithms are used in studies to detect and manage diseases in fruits, vegetables, and field crops early. CNN models are more sensitive to key features and can analyze leaf diseases [11], Due to its several feature extraction processes, Accurate categorization is produced using CNN deep learning. The most recent Deep CNNs and meta-architectures, including VGG Nets, Le-nets ResNet, R-CNN, Mask R-CNN, FCN, SSD, and other well-known object identification and segmentation architectures, were used to forecast tomato leaf disease. But they moved too slowly to produce better outcomes. These developments made the Convolutional Neural Network faster and more accurate. CNN leaf disease detection architecture is shown in Figure 3.

4.1 LeNet

After a first fully linked layer, the LeNet design moves onto convolutional and pooling layers. By adopting a condensed connection layer known as max-pooling to reduce picture size between convolutional layers, overfitting can be avoided and CNNs can train more effectively [12]. It has been used to recognize handwritten numbers, traffic signs, and even human faces [13]. The LeNet CNN is a straightforward but efficient model. Even though LeNet's design hasn't evolved much since it was built more than 20 years ago, it is still in broad usage as seen in Figure 4.

In order to classify images, the LeNet convolutional neural network (CNN) architecture is frequently utilized. It is less useful for tomato leaf disease detection than more advanced designs. This article explains LeNet and provides pertinent examples of its use:

LeNet design is LeNet has convolutional, pooling, and classification layers. For preliminary image categorization, the architecture is simple and efficient. Modern CNN architectures have more layers and parameters. It also classifies plant diseases and identifies plant stress. Such as: In "A Review on Detection of Plant Diseases using Image Processing Techniques," tomato diseases were classified using LeNet. The researchers diagnosed several illnesses using LeNet on tomato leaf photos.

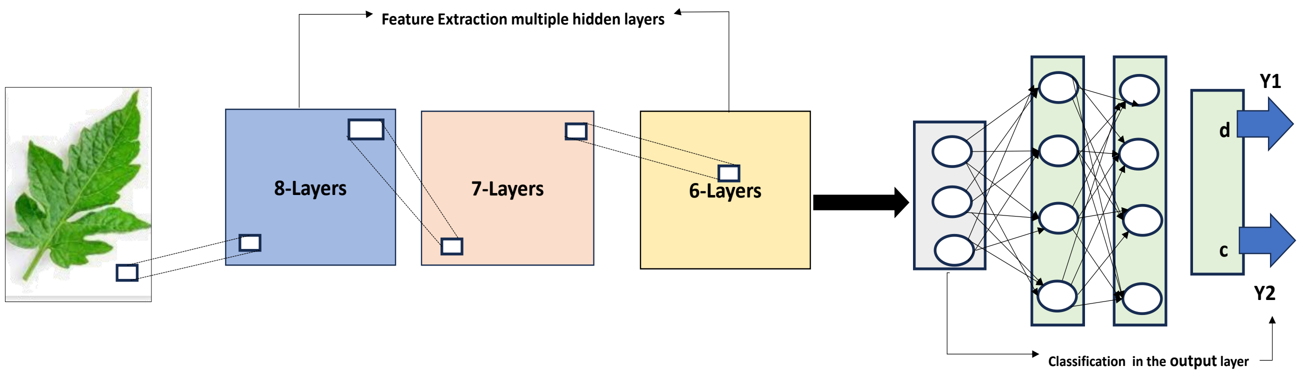

Figure 3. Deep convolutional neural networks architecture

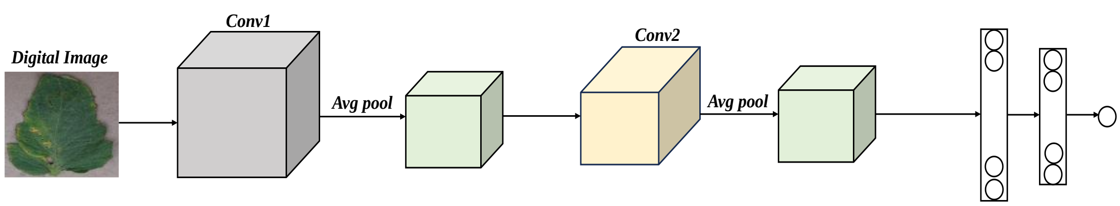

Figure 4. LeNet architecture

Limits and Challenges:

LeNet may miss subtle patterns and subtleties due to its shallowness. Tomato leaves might hide modest diseases signals.

LeNet's simplicity may prevent it from representing all tomato leaf disease features and variants, resulting in lower accuracy than more complicated structures.

Lighting, camera position, and disease type can complicate tomato leaf disease data. LeNet could find this complexity challenging. Pre-trained models for tomato leaf disease detection may be harder to find because LeNet is an older design than other models. Recent CNN architectures like ResNet, VGGNet, and GoogleNet have become popular due to their deeper structures and improved performance. These patterns help researchers detect complex diseases and improve precision.

Thus, while LeNet can still be utilized for tomato leaf disease identification, academics and practitioners prefer more contemporary systems tailored for disease detection and other complex image classification tasks.

4.2 GoogleNet

There are a total of 27 layers in the GoogleNet Model in Figure 5. Others, such as the Convolutional and Fully-Connected layers, are parameterized while others, such as the Max-Pooling layer, are not. This module is built using a variety of tiny convolutions that greatly minimize the number of parameters. Their method is based on a 22-layer deep CNN even though they reduced the number of parameters from 60 million (Alex Net) to merely 40 million.

GoogleNet, a CNN architecture that pioneered Inception modules, categorizes images quickly and accurately. It has been used in comparable conditions but not to detect tomato leaf infections. GoogleNet is introduced and used to identify tomato leaf diseases. Inception modules distinguish GoogleNet Architecture. These modules' several filter sizes (1×1, 3×3, and 5×5) and parallel convolutions collect features at different scales. It maximizes calculation speed and precision. GoogleNet, a member of the Inception family, has been used to detect tomato leaf diseases. This architecture has been used for plant disease classification, but tomato leaf disease detection is rare. Some examples: The researchers [14] used GoogleNet to classify diseases of plants including tomato leaf diseases.

Challenges and Limitations:

There is a dearth of material dedicated to the detection of tomato leaf diseases using GoogleNet or Inception architecture. This points to the necessity for specialized study in this area.

Fewer pre-trained models may be available for tomato leaf disease detection using GoogleNet than other popular architectures such as ResNet or VGGNet. This can make it harder to learn and adopt new skills.

The availability, breadth, and diversity of datasets on tomato leaf diseases varies widely. An enormous quantity of labeled data is typically required to successfully train a deep architecture like GoogleNet. Performance and generalization may be affected if the dataset is small or unbalanced.

Deeper designs, such as GoogleNet, can be computationally intensive due to their intricate design. It can be difficult to conduct training and inference in contexts with limited resources due to the potential need for increased processing resources, such as high-end GPUs.

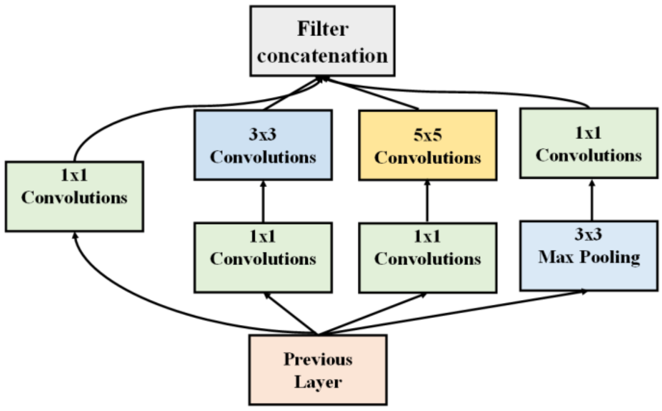

Figure 5. Google net architecture

4.3 AlexNet

Although AlexNet is larger and more complex than LeNet, the network architecture shown in Figure 6 is remarkably comparable to the use of numerous Convolutional Layers. Soon after its first release, the AlexNet architecture demonstrated excellent performance when used with big image datasets. AlexNet includes five convolutional layers in total, including two dropout layers, three fully connected layers, and two max-pooling levels.

In 2012, Alex Krizhevsky & colleagues announced AlexNet, a revolutionary CNN architecture. In order to identify plant diseases and generally classify images, it has been widely used. Use AlexNet to detect tomato leaf disease. The AlexNet architecture consists of convolutional, maximum pooling, and totally linked layers. Deep learning became well-known in computer vision thanks to the ground-breaking result of the ImageNet Large-Scale Visual Recognition Challenge.

Diagnostics for Plant Disease Although AlexNet has achieved success in more challenging plant disease detection tasks, there are few examples of tomato leaf disease detection. Some instances: According to the study "Plant Disease Recognition Using a Convolutional Neural Network," Alex Net was able to identify tomato plant diseases such citrus canker and bacterial leaf spot. The classification of disorders was excellent. The study [15] used AlexNet as a feature extractor.

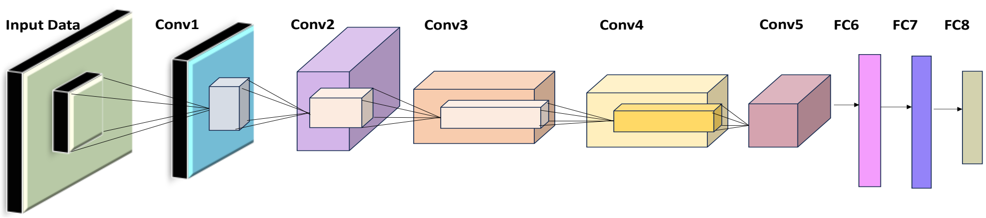

Figure 6. AlexNet architecture

Issues and Limitations: Applying AlexNet to tomato leaf disease detection or similar activities has various issues and limitations.

4.4 VGGNet

Input images up to 224×224 pixels in size can be processed using its 4096 convolutional features. While VGGNet excels at particular tasks, Large-filter CNNs are not the ideal solution for most image classification problems; CNN designs like Google Net's AlexNet architectures. This is particularly the case for input photographs ranging in size from 100×100 to 350×350 pixels [16] as seen in Figure 7. The VGGNet CNN architecture competed and won the ILSVRC 2014 classification competition, demonstrating its usefulness in real-world applications. When it comes to computer vision, many applications can benefit from the use of VGG CNN because of its processing efficiency [17]. It can be employed, among other things, for object detection. Its comprehensive feature representations are useful for many kinds of neural network architectures (YOLO, SSD, etc.).

VGGNet is a deep convolutional neural network design. A well-known image classification is VGGNet. tool and plant disease detection, although tomato leaf disease detection applications are scarce. VGGNet may identify tomato leaf disease. The uniform VGGNet Architecture has numerous convolutional layers with modest 3x3 filters followed by max pooling layers.

Plant diseases, in particular leaf diseases, have been successfully identified by VGGNet. There aren't many instances, despite the fact that VGGNet's ability in identifying plant diseases suggests it might be used to identify diseases in tomato leaves. Some instances: In "Deep Learning Approaches for Plant Disease Detection and Diagnosis," scientists examined tomato leaf disease using the VGGNet architecture.

In the study [18] classified using VGGNet, successfully diagnosed disorders of tomato leaves. Transfer learning was used to enhance a pre-trained VGGNet model for precise disease classification on a dataset of tomato leaf diseases.

Challenges and Limitations: Using VGGNet for tomato leaf disease detection or related tasks, such as Due to its complex nature, VGGNet has more parameters than other architectures. In order to train and infer with a VGGNet, powerful GPUs and CPUs are required.

4.5 ResNet-101

Simple two of the deep learning problems that ResNet was used to tackle at Microsoft Research Asia in 2016 and 2017 were statement completion and machine understanding [19] as seen in Figure 8. Disciplines in ResNet Both ResNet-50 and ResNet-101 are supported. Microsoft's machine comprehension system uses CNNs to respond to one hundred thousand inquiries across twenty different domains. To match the processing power of GPUs, ResNet's CNN design may be scaled to meet your needs.

Microsoft Research developed ResNet-101, a CNN architecture. ResNet-101 is frequently used in image despite the limited applications for tomato leaf disease detection, categorization and plant disease detection are both possible. Using ResNet-101, tomato leaf disease may be found. ResNet-101 Architecture is 101-layer ResNet, among others Residual connections let the network learn residual mappings and solve the vanishing gradient problem. These connections help train deep networks and collect complicated information. ResNet-101 has effectively detected plant diseases, including leaf diseases. Although ResNet-101's efficacy in detecting plant diseases supports its usage in detecting tomato leaf diseases, there aren't many examples. As an instance, consider [20] to identify tomato leaf disease, employed ResNet-101. With the use of a skilled ResNet-101 model, tomato leaf diseases could be distinguished with a high degree of accuracy [20, 21].

Challenges and Limits:

ResNet-101 has some drawbacks when used for tomato leaf disease detection:

ResNet-101 is a deep architecture with several levels and parameters. ResNet-101 requires high-end GPUs for training and inference.

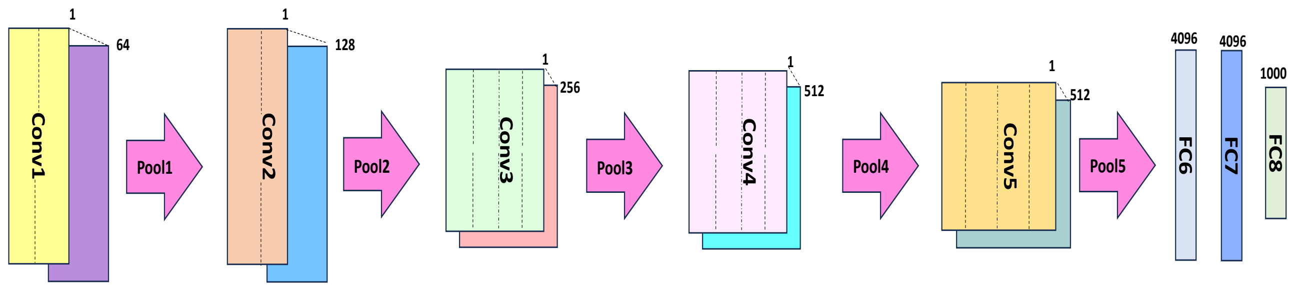

Figure 7. VGGNet architecture

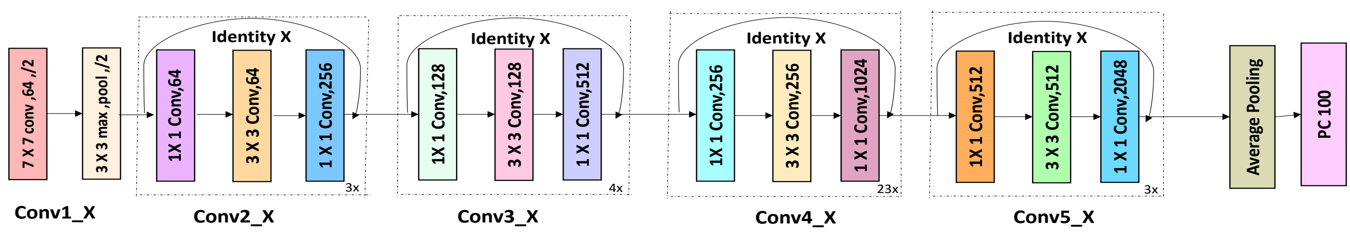

Figure 8. ResNet101 architecture

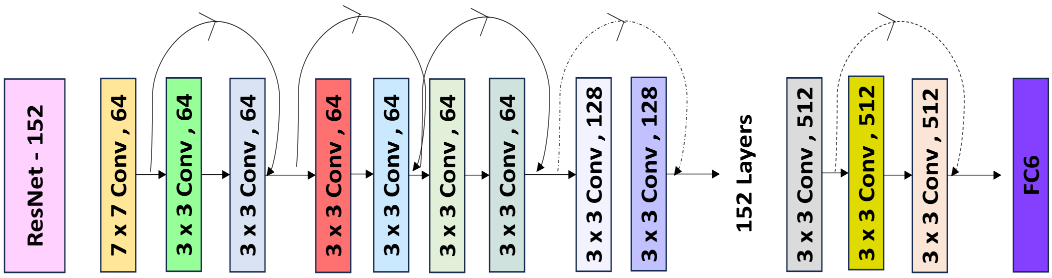

Figure 9. ResNet152 architecture

4.6 ResNet-152

By learning the residual representation functions rather than the signal representation directly, ResNet-152 can have an extraordinarily deep network with up to 152 layers, as seen in Figure 9. ResNet-152 uses a skip connection, also known as a shortcut connection, to transport data directly from one layer to the next without altering it in any way [20-22].

While both AlexNet and ResNet-152 use over 60M parameters, the top-five accuracy between the two networks is roughly 10% different. ResNet-152 training, however, necessitates a great deal of calculations (about 10 times that of AlexNet), necessitating longer and more taxing training sessions. With more parameters and FLOP than ResNet-152, VGGNet also performs worse. Training an inaccurate VGGNet requires more time.

Table 1. Statistical features comparison of different CNN architectures

Architectures	Overfitting	Size and Diversity of Dataset	Interpretability
VGGNet	May be prone to overfitting	Beneficial with moderate dataset size	Intermediate interpretability
AlexNet	Less prone to overfitting	Relatively forgiving of dataset size	Relatively interpretable due to simplicity
GoogleNet	May be prone to overfitting	Beneficial with moderate dataset size	Reduced interpretability due to Inception modules
LeNet	Less prone to overfitting	Suitable for smaller datasets	Relatively interpretable due to simplicity
ResNet-101	Prone to overfitting	Requires large and diverse dataset	Reduced interpretability due to depth
ResNet-152	Prone to overfitting	Requires large and diverse dataset	Reduced interpretability due to depth

Deep convolutional neural network (CNN) ResNet-152 makes use of ResNet (Residual Network). For general image categorization and plant disease detection, ResNet-152 has been extensively employed. The 152-layer ResNet architecture is known as ResNet. The network can learn residual mappings and resolve the vanishing gradient problem thanks to residual connections. These connections aid in the training of deep networks and the acquisition of complex data. Plant Disease Detection ResNet-152 has been used to detect plant diseases, although tomato leaf disease detection instances are scarce. However, the architecture's plant disease detection capabilities suggest its use for tomato leaf diseases. It is [23, 24] used a ResNet-152 version to detect plant diseases. The study showed ResNet-152's accuracy in diagnosing plant diseases, not just tomato leaf diseases.

Challenges and Limitations: When using ResNet-152 for tomato leaf disease detection or related tasks, consider the following:

ResNet-152 is a deep architecture with several layers and parameters. High-end GPUs are needed for ResNet-152 training and inference.

The Table 1 represents the comparison different CNN architectures with respect to statistical features.

5. CNN MODEL IMPLEMENTATION

The classification processes were substantially accelerated and the detection rate was raised by using CNN algorithms. On the basis of the top two best CNN models, which are employed and tested, a model will be developed to enhance CNN's performance and general accuracy. The ResNet-152 residual network is utilized as the main model once VGGNet and ResNet-101 have been installed. In the experiment, leaf diseases position features were automatically collected by convolutional layers, and iterative learning was used to categorize the disorders. ResNet-152 surpasses the models in terms of object detection precision and error rate as well as eliminating the issue of gradient fading during testing by omitting the appropriate layers.

Table 2. Classes data summary of training, validation, and testing

S.No.	Class	Data Testing	Data Training: Training	Data Training: Validation
1	Bacterial Spot	341	1089	272
2	Mosaic Virus	60	192	47
3	Early Blight	160	512	128
4	Target Spot	225	487	121
5	Healthy	255	815	203
6	Late Blight	306	977	244
7	Spider Mites	269	719	179
8	Leaf Mold	284	907	226
9	Septoria Leaf Spot	284	858	214
10	Yellow Leaf Curl	858	2743	685

Using CNN algorithms significantly increased the detection rate and sped up the classification operations. In order to improve CNN's performance and overall accuracy, a model will be constructed based on the top two best CNN models, which are currently being used and tested. Once VGGNet and ResNet-101 are implemented, the ResNet-152 residual network is used as the primary model. In the experiment, leaf illness position features were automatically collected by convolutional layers, and iterative learning was used to categorize the disorders. By skipping the necessary layers, ResNet-152 outperforms the models in terms of object detection accuracy and error rate as well as resolving the problem of gradient fading during testing. As can be seen in Table 2, evaluators engage in activities such as data acquisition, data cleaning, and data classification.

6. RESULTS AND DISCUSSIONS

For the proposed study, we developed a convolutional neural network (CNN)-based model for disease identification in tomato crops. The suggested CNN-based design uses three convolution and maximum pooling layers with different numbers of filters. The PlantVillage dataset provided us with data on tomato leaves that we utilized in our tests. The dataset includes nine distinct diseases and a tenth "healthy" category. We employed data enhancement methods to ensure that each student had access to an equivalent number of high-quality images, and we evaluated CNN models and calculated corresponding evaluation parameters based on each disease class

The PlantVillage Dataset provided the input data. One healthy label and nine disease labels (which include information about bacterial spot, black leaf mold, gray leaf spot, late blight, and powdery mildew) make up the 10 classes or labels in the data set. As seen in Table 2, the original dataset contains 14,529 images of tomato leaves in various arrangements.

As per Table 2, out of the total of 14,529 pieces of information, 80% will be set aside for use in the training phase, and 20% will be used in the testing phase, respectively. The validation data section will make up 80% of the whole, whereas the testing data component will only make up 20%.

ResNet-152's performance is compared to that of ResNet-101, VGGNet, GoogleNet, AlexNet, and LeNet using a variety of criteria, including Accuracy and Precision, Recall, F1-Score. The metrics for the comparable models were gathered and are explained below.

1. Accuracy: The ratio of accurate reports to all predictions is known as accuracy.

The number of times the model is accurate when the predicted label matches the actual label. A false negative occurs when a model predicts the incorrect label for a specific case. The number of cases where the model accurately predicted a false label despite the fact that the actual label was true is referred to as the "True Negative". The number of False Positives in Eq. (1) is the number of occasions where the model correctly predicted the label but the label was incorrect.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

2. Precision: By dividing the total number of positive predictions by the number of correct forecasts in Eq. (2), as shown in Table 3, one can determine the accuracy of a model's class predictions.

$$\text{Precision} = \frac{TRUE\ POSITIVE}{TRUE\ POSITIVE+FALSE\ POSITIVE} \tag{2}$$

The proportion of the test set's total examples that belong to each class is used to calculate that class's weight.

3. Recall: Correctly identified observations as a percentage of total observations are one definition of accuracy in Eq. (3). The problem is that class differences in performance may not be accurately reflected. As a result, in Table 3, accuracy is just one of several metrics used to rank models these days.

$$\text{Recall} = \frac{TRUE\ POSITIVE}{TRUE\ POSITIVE+FALSE\ NEGATIVE} \tag{3}$$

4. F1-Score: If the F1 score is high, then means the output forecasts are accurate with few erroneous positive and negative results. When the F1 score drops below Table 3, the model is considered a complete failure in Eq. (4).

$$\text{Recall} = \frac{TRUE\ POSITIVE}{TRUE\ POSITIVE+FALSE\ NEGATIVE} \tag{4}$$

The evaluated CNN model of ResNet-152, ResNet-101 and VGGNet calculated the corresponding evaluation parameters based on each disease class, as shown in Figures 10-12.

In conclusion, both the ResNet-152 and the ResNet-101, both of which are VGGNet neural networks, have been implemented. The following factors can be taken into account when comparing ResNet-152, ResNet-101, and VGGNet for tomato leaf disease detection:

Table 3. Accuracy classes summary of precision, F1-score and recall for ResNet-152, ResNet-101 and VGGNet

Class	Precision			F1-Score			Recall		
	ResNet-152	ResNet-101	Vgg Net	ResNet-152	ResNet-101	Vgg Net	ResNet-152	ResNet-101	Vgg Net
Bacterial spot	0.95	0.95	0.94	0.96	0.96	0.95	0.98	0.98	0.98
Spider Mites	0.94	0.94	0.93	0.99	0.98	0.96	0.99	0.98	0.97
Early Blight	0.96	0.95	0.95	0.95	0.96	0.98	0.97	0.99	0.98
Target Spot	0.99	0.98	0.98	0.97	0.98	0.97	0.97	0.98	0.96
Late Blight	0.94	0.97	0.94	0.97	0.97	0.97	0.97	0.97	0.97
Mosaic Virus	0.98	0.96	0.97	0.99	0.98	0.98	0.99	0.98	0.97
Leaf Mold	0.97	0.98	0.96	0.98	0.99	0.97	0.98	0.97	0.96
Septoria Leaf Spot	0.96	0.99	0.98	0.96	0.97	0.98	0.99	0.99	0.98
Yellow Leaf Curl	0.98	0.97	0.97	0.99	0.98	0.98	0.98	0.97	0.98

The computing requirements of ResNet-152 and ResNet-101 are high because of their depth and number of parameters. It's important to note that VGGNet, especially in its deeper iterations, can be very computationally demanding.

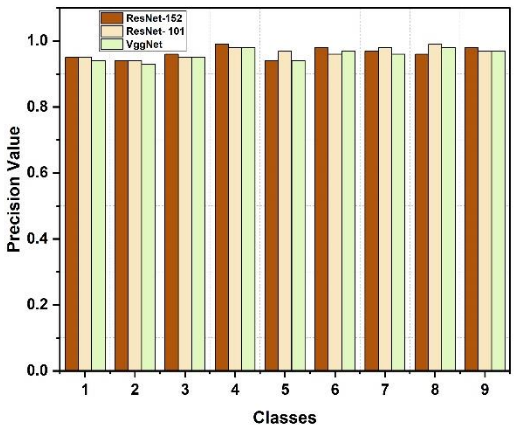

Figure 10. Performance evolution metrics for precision

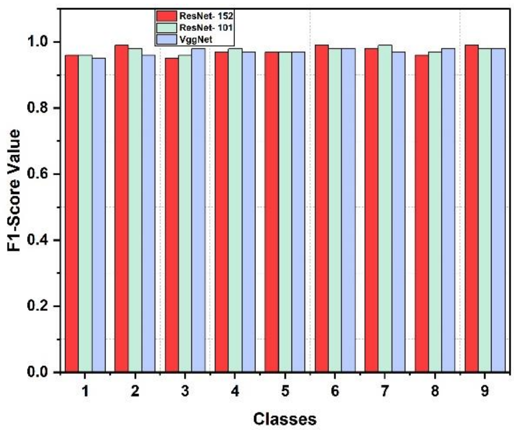

Figure 11. Performance evolution metrics for F1-score

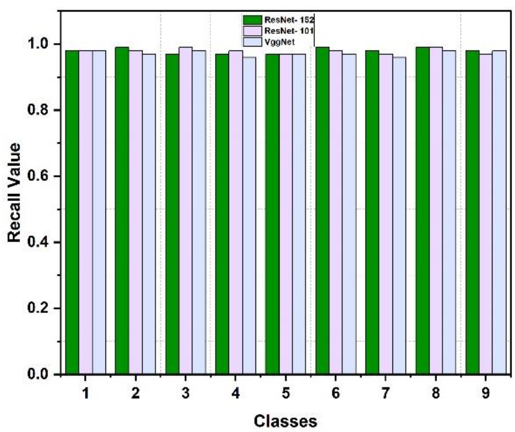

Figure 12. Performance evolution metrics for recall

The more sophisticated and abstract properties of tomato leaves can be captured by models like ResNet-152 and ResNet-101. Tomato leaf disease traits are among those that can be captured by VGGNet's uniform design and tiny convolutional filters.

The increased complexity of deeper architectures like ResNet-152, ResNet-101, and VGGNet makes it more difficult to evaluate the learnt features and their connection to disease patterns in tomato leaves. These designs are popular because they can use pre-trained models. Rather than spending instead of spending more time and effort learning from scratch, you can use these pre-trained models and refine them using transfer learning on particular datasets related to tomato leaf disease.

The available dataset, computational resources, and the intended trade-off between accuracy and efficiency are only a few of the elements that influence the selection of the design. VGGNet strikes a good mix between depth and interpretability, while ResNet-152 and ResNet-101 give greater depth and may be able to capture more nuanced features. When deciding on an appropriate architecture for the tomato leaf disease detection task, it is important to consider both the availability of pre-trained models and the task-specific needs.

Their accuracy on pre-trained networks has been tested using 50 and 80 epochs, and records of a range of events have been kept. ResNet-152 has been successfully trained to categorize Utilizing pictures of tomato plant leaves from the plantvillage dataset, a variety of diseases that can harm tomato plant leaves are shown. The best classification performance can be reached when ResNet-152 is trained with a variety of various batch sizes. Additionally, the experiment results show that it is possible to get the highest accurate categorization performance with a learning rate of 0.001 and a data division ratio of 80% to 20% between training and testing. In preparation for future work, each and every class in the Plant Village Data set will be tasked with identifying each and every sickness.

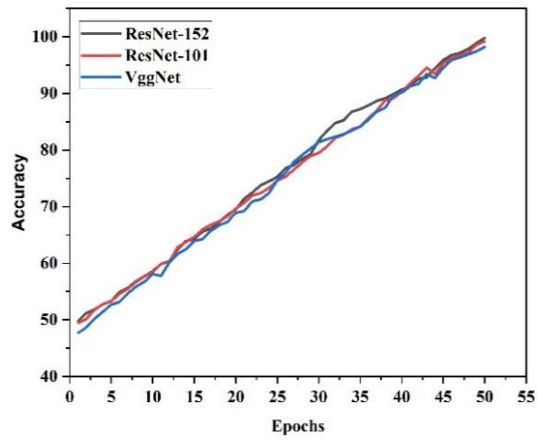

Figure 13. Instance I with 50-epochs

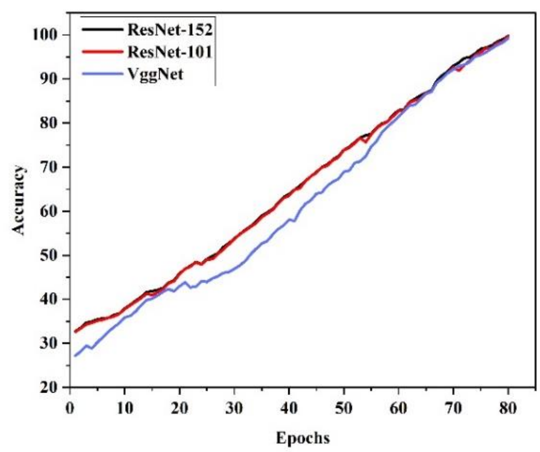

Figure 14. Instance-I with 80-epochs

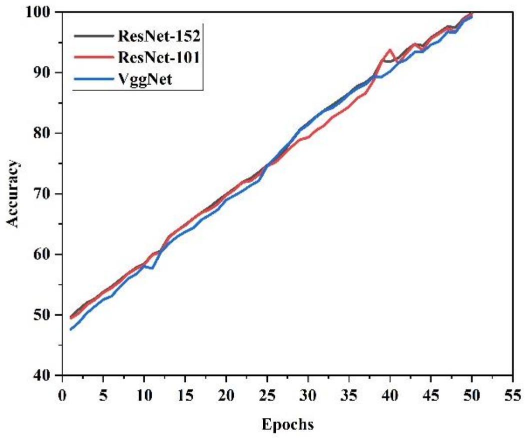

Figure 15. Instance-II with 50-epochs

The graphs in Figures 13-16 are drawn based on the result obtained, that reveals, irrespective of the epochs and instances ResNet-152 is found to have the highest accuracy than ResNet-101 and VGGNet at most of the points.

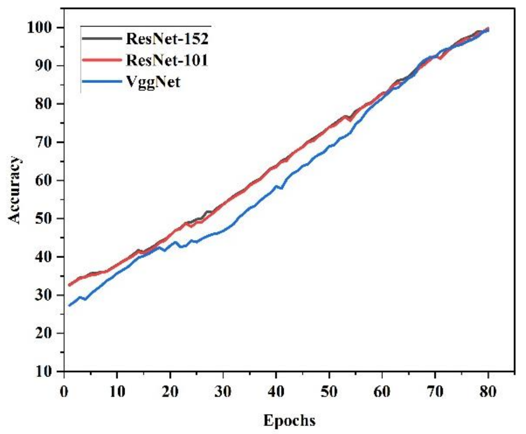

Figure 16. Instance-II with 80-epochs

7. CONCLUSIONS

Nowadays, numerous challenges are faced by farmers in agriculture. Speedy and accurate detection of leaf diseases could indeed assist in meeting the constantly expanding requirement for tomato production. Deep learning-based approaches yield very good results in tomato leaf disease classification. In this regard the present research work implemented ResNet-152 and ResNet-101, both of which are VGGNet neural networks. The computing requirements of ResNet-152 and ResNet-101 are high because of their depth and number of parameters. It's important to note that VGGNet, especially in its deeper iterations, can be very computationally demanding. The increased complexity of deeper architectures like ResNet-152, ResNet-101, and VGGNet makes it more difficult to evaluate the learnt features and their connection to disease patterns in tomato leaves. These designs are popular because they can use pre-trained models. Rather than spending additional time and energy training from scratch, you may utilize these pre-trained models and fine-tune them on specific tomato leaf disease datasets through transfer learning. When deciding on an appropriate architecture for the tomato leaf disease detection task, it is important to consider both the availability of pre-trained models and the task-specific needs. Furthermore, the results proved the superiority of the experimental performance when compared with earlier research conducted for tomato leaf disease classification.

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