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Disease Detection of *Solanum Lycopersicum* using SqueezeNet Deep Learning Architecture

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Abstract:
The productivity of a nation's food supply hinges on the health of its crops, and plant diseases can have a severe impact on food production. Early detection of these diseases is vital, and this can be achieved through analyzing images of plant leaves. Advances in deep learning have notably enhanced the detection of plant diseases. This study introduces SqueezeNet for classifying diseases in Solanum Lycopersicum (tomato plants) and compares its performance to other advanced deep learning models. The research involved classifying leaves into ten disease categories, using the augmented plant Village dataset for training, validation, and testing via transfer learning. The results showed that SqueezeNet1_0 and SqueezeNet1_1 achieved the highest test accuracies of 99% and 99.8%, respectively, outperforming other models like VGG16, GoogLeNet, EfficientNet B0, and ResNet50.

Keywords: Deep Learning, *Solanum Lycopersicum*, SqueezeNet, Tomato Plant Disease, Transfer Learning

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1. Introduction

As a developing country, India largely depends on agriculture and allied activities. It is the primary source of income for 58% of Indians [1]. India with approximately 1.4 billion people is the second most populous country in the world [2]. This mammoth population has increased the demand for food and simultaneously needed production much faster. Thus, agricultural and allied sectors are required to increase production to meet the elevated demands of the people continuously.

Tomato is an edible berry of a plant, which is scientifically known as *Solanum lycopersicum*. It is a culinary vegetable served as a main course meal or salad. The sourness of Indian Cuisine comes from tomatoes which are staples in foods. They are also used in preserved products like sauce, soup, paste, ketchup, etc. Besides its taste, the tomato has many health benefits. It contains an important antioxidant *lycopene* which helps to reduce the risk of getting cancer or heart disease. It also contains Vitamin C which along with *lycopene* can reduce stress-related symptoms and inflammation of the skin [3, 4]. India is a leading tomato producer country in the world. Tomato is a short-duration crop and gives a high yield. This yield of the tomato plants can get affected by several diseases which may be bacterial, fungal, and viral. Some common types of diseases are Bacterial Spot, Early blight, and Leaf mold. Bacterial spots are lesions that start as small water-soaked spots and merge to form necrotic areas on leaves. These disease-infected plants usually have a blighted appearance. In India, bacterial spots cause an annual loss of 10-20%, which may go up to 80% in rare cases [5, 6]. Early blight is a fungal disease that causes tomato plants to have oval-shaped lesions with yellow chlorotic regions across the lesion. Leaf mold is also a fungal disease that makes the older leaves exhibit pale greenish to yellow spots on the upper surface. Detection of the disease of the plants at an early stage is of utmost importance to increase the yield of tomatoes. If disease identification is done accurately, we can prevent further contamination using the correct pesticides and other chemicals. It is reported, among the various parts of the plant, only leaves are most prone to show the symptoms of diseases. The color of leaves is of prime importance when diagnosing physiological status under various conditions [7].

In the past, farmers had to rely on their own observations, examining the leaves with the naked eye, or they had to hire specialists such as plant pathologists to detect and diagnose diseases. This method was highly labor-intensive and the accuracy of such diagnoses was often questionable. However, the advent of Deep Learning and Computer Vision has simplified many tasks that were previously time-consuming and challenging. With Computer Vision, detecting plant diseases has become significantly easier. This technology can efficiently extract features from images of diseased plants and accurately identify them.

Today, Deep Learning is applied in a wide range of fields, from entertainment and healthcare to self-driving cars. In recent years, substantial progress has been made in developing various deep learning architectures for image classification, including AlexNet, GoogLeNet, and VGGNet.

One significant drawback of Deep Learning is the requirement for large amounts of training data and the considerable time needed to train deep neural networks.

Recognizing the importance and relevance of this issue, the proposed study focuses on detecting

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and identifying diseases in tomato plants using the SqueezeNet deep learning architecture. This architecture employs transfer learning, allowing the model to be trained more quickly and accurately. The performance of SqueezeNet is compared with other state-of-the-art architectures such as VGG16, ResNet50, GoogLeNet, and EfficientNet B0. Section 2 reviews the existing work related to this study. The proposed research methodology is outlined in Section 3. Section 4 presents the results and discussion of the study. Finally, the study concludes in Section 5.

2. Related Work

Numerous studies have explored the detection and classification of various plant diseases. While tomatoes are a major vegetable crop in India, research specifically focused on tomato plant diseases is relatively limited compared to studies on general plant diseases. This section reviews the methods and research conducted by various authors in the field of plant disease detection

3. Proposed Research

In this paper, I have utilized the Tomato dataset from the augmented plant Village dataset. The concept of transfer learning has been applied to train CNN architectures to overcome the disadvantage of the huge training time requirement for Deep Learning models. Transfer Learning also leverages the features learned from training on a similar large dataset and averts the process of learning from the beginning which in fact can also result in getting greater accuracy. The dataset has been trained, validated, and tested on different state-of-the-art CNN architectures. The SqueezeNet1_0, SqueezeNet1_1, VGG16, GoogLeNet, ResNet50, and EfficientNet B0 pre-trained architectures have been used as models.

3.1 Dataset

The tomato plant Village dataset, mentioned above, has 61,486 leaf images for 39 unique plant diseases. The augmented plant Village dataset was created using 6 augmentation techniques which include scaling, rotation, gamma correction, noise injection, image flipping, and PCA color augmentation. The Tomato plant dataset consists of 18,845 images for 9 types of plant diseases and healthy plant leaves - Bacterial spot, Early blight, Late blight, Leaf Mold, Septoria leaf spot, Spider mites Two-spotted spider mite, Target spot, Tomato mosaic virus, Yellow leaf curl virus, and Tomato healthy leaves. Some of the examples of images of the tomato dataset are shown in Fig. 1.

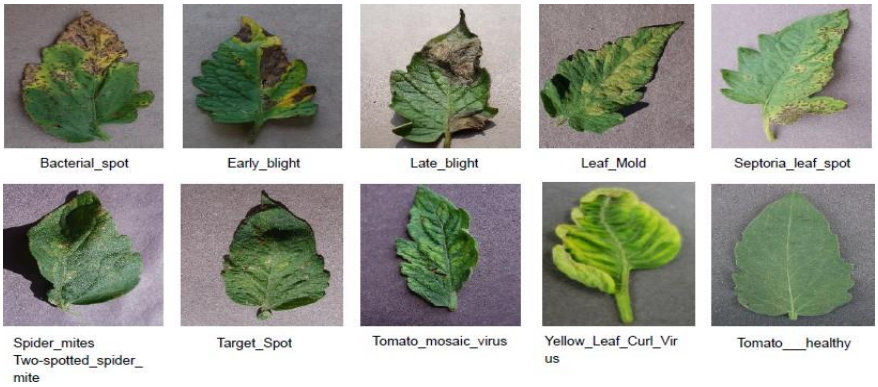

Fig. 1 Images of different tomato plant diseases

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Diseases	Total	Train (80%)	Validation (10%)	Test (10%)
Bacterial_spot	2127	1701	212	214
Early_blight	1000	800	100	100
Late_blight	1909	1527	190	192
Leaf_Mold	1000	800	100	100
Septoria_leaf_spot	1771	1416	177	178
Spider_mites Two-spotted_spider_mite	1676	1340	167	169
Target_Spot	1404	1123	140	141
Yellow_Leaf_Curl_Virus	5367	4293	536	538
Tomato_mosaic_virus	1000	800	100	100
Tomato_____healthy	1591	1272	159	160

Table 1 Number of images of different diseases

Table 1 shows the created distribution of images for different plant diseases.

3.2 State-of-the-art CNN architectures

Different state-of-the-art CNN architectures compared with SqueezeNet architecture are VGG16, ResNet50, GoogLeNet, and EfficientNet B0.

1) VGG16

VGG16, a variant of VGG16 model [24] has 19 layers. It has 16 convolution layers, 3 Fully Connected layers, 5 MaxPool layers, and 1 SoftMax layer. It has won the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC 2014). This architecture uses a 3X3 kernel size with a stride of 1 and the spatial resolution is preserved by adding spatial padding. The Max Pooling layers have 2X2 filters with a stride of 2. It is followed by Rectified Linear Unit (ReLU) to add non-linearity to the model. This model takes input image size as 224X224 pixels. A schematic diagram of VGG16 architecture is shown in Fig. 2.

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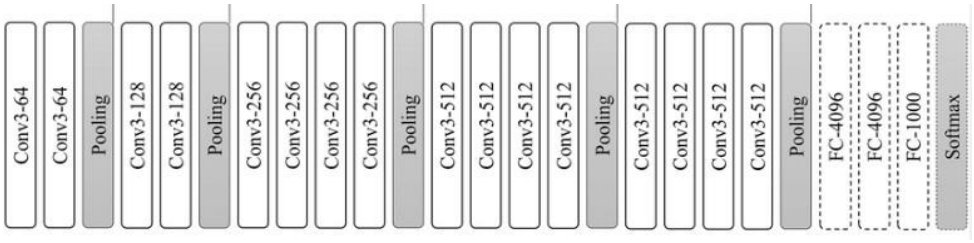

Fig. 2 Diagram of VGG16 Architecture

2) ResNet50

ResNet50 is a widely used variation of the ResNet model. It has 48 Convolution layers with 1 MaxPool and Average Pool layer. Thus, the architecture has 50 layers. Training ultra-deep neural networks were made possible due to the framework of ResNets. ResNet50's building block has a bottleneck pattern that reduces the number of parameters and matrix multiplications. It introduced a deep residual learning framework to solve the problem of getting more errors when the model gets deeper. This model takes an input of 224X224 pixel images. Fig. 3 represents a schematic diagram of ResNet50 architecture.

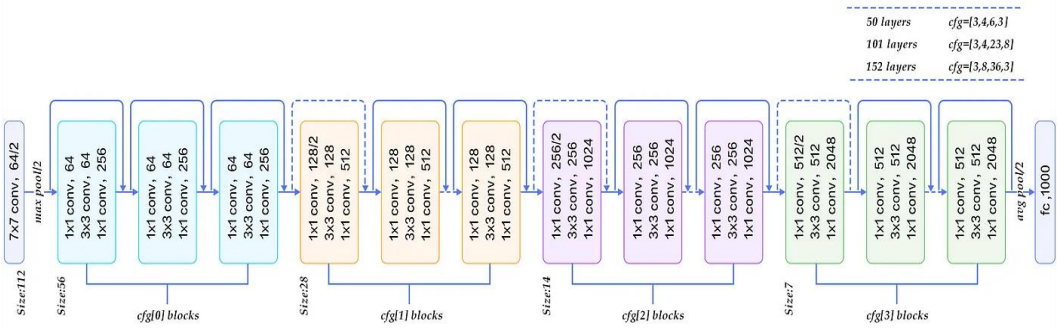

Fig. 3 Diagram of ResNet50 Architecture

3) GoogLeNet

GoogLeNet won the ILSVRC competition in 2014. Google proposed the architecture GoogLeNet. The total model is 22 layers deep and has 27 pooling layers. 9 Inception modules are stacked linearly and their ends are connected to the global average pooling layer. The architecture takes an input of 224X224 image size. A diagram of GoogLeNet architecture is shown in Fig. 4.

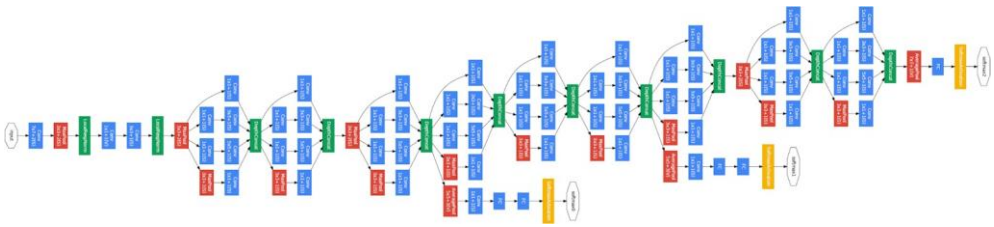

Fig. 4 Diagram of GoogLeNet Architecture

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4) EfficientNet B0

EfficientNet architecture was designed to be more efficient in terms of computation and memory usage, while still achieving high accuracy on the image classification tasks. The architecture of the EfficientNet consists of blocks of multiple layers of depth wise separable convolutions, followed by point wise convolutions, and a skip connection. The blocks are repeated several times, and the number of blocks, as well as the number of filters in each block, are adjusted based on the scaling coefficients. An architectural diagram of the model is given in Fig. 5.

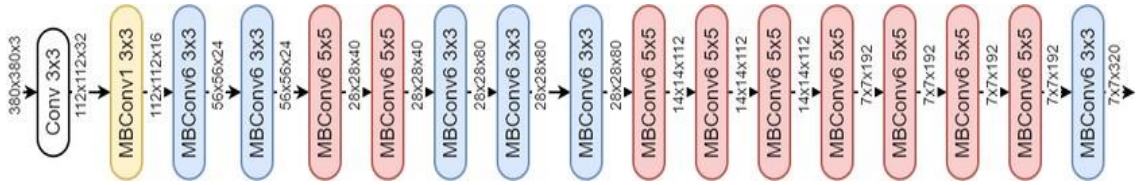

Fig. 5 Diagram of EfficientNet B0 Architecture

5) SqueezeNet

SqueezeNet is a Deep Learning architecture for Convolutional Neural Networks (CNNs). It is best known for being lightweight and fast while maintaining a reasonable accuracy level for image classification tasks. Despite having 50 times fewer parameters than AlexNet, it still achieves accuracy comparable to AlexNet. It was designed with the goal of being small enough to run on resource-constrained devices such as smartphones and embedded systems.

SqueezeNet is based on the following features:

- It uses 1X1 filters instead of conventional 3X3 filters. This reduces the model's parameters by 9 times.
- Number of input channels to 3X3 is decreased with the help of a squeeze or bottleneck layer.
- Larger activation map can be created by applying it to down sample later.

The architecture of SqueezeNet is based on the concept of "squeezing" the spatial dimensions (width and height) of the feature maps while retaining the depth (number of filters). This reduces the number of parameters in the network, making it faster and more computationally efficient. Additionally, SqueezeNet uses a different kind of layer called a "fire module", which consists of a squeeze layer followed by an expanded layer, to increase the number of filters in the network efficiently. Fig. 6 shows a diagram of SqueezeNet architecture.

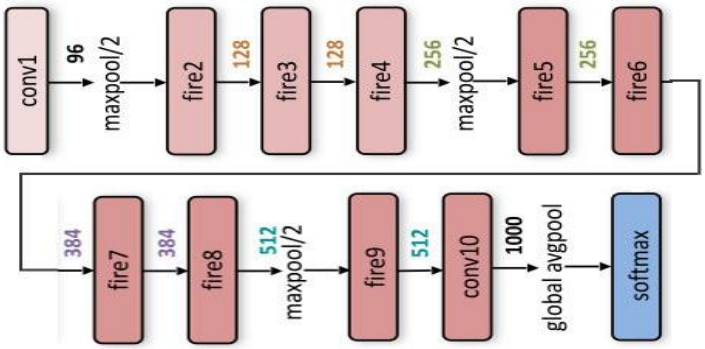

Fig. 6 Diagram of SqueezeNet Architecture

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3.3 Experiment

The models in this study were implemented using PyTorch. The experiment was conducted on Google Colaboratory and was compiled using GPU.

The Tomato plant disease data from the PlantVillage dataset was divided into three parts: Training, Validation, and Test dataset having 80% (15,072), 10% (1,881), and 10% (1,892) of the total dataset (18,845) respectively.

All CNN architectures are implemented using transfer learning in this research work. The CNN architectures are pre-trained models on the ImageNet dataset. They leveraged the features learned from ImageNet to identify and classify all categories of plant disease in the dataset. Here, the pre-trained models were given an input image size of 224X224 pixels. The batch size for all models was 8. Optimizer used in models was SGD with a momentum of 0.9. The loss function applied was Cross entropy loss. Learning rates for VGG16, GoogLeNet, Efficientnet B0, ResNet50, SqueezeNet1_0, and SqueezeNet1_1 models were 0.01, 0.001, 0.001, 0.01, 0.001, and 0.001 respectively. Every model has been trained for 25 epochs and then validated to fit models and tested on the validation and test dataset which the model has never seen.

3.4 Performance Metrics

As the dataset contained 10 unique classes of Tomato disease, the classification was an example of a multi-class classification problem. A confusion matrix has been created for each model. The Confusion Matrix relied on True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values to measure a model's performance. TP signified that the test results correctly predicted the existence of a condition. FP denoted a test result that falsely indicates a condition was present. TN is interpreted as a test result correctly indicating an absence of a condition. FN is a test result that wrongly specifies a particular condition that is absent. The confusion metrics for models used in this study are shown in Fig. 7.

In this study, the performance of SqueezeNet and other CNN models were computed using metrics such as Accuracy, Precision, Recall, and F1 Score. Accuracy was the most popular metric used to evaluate a model. It is the number of correct predictions over the total number of predictions. Precision measured the number of positive predictions made those were correct (TP). The recall was the number of positive cases correctly predicted by the model. The harmonic mean of precision and recall is called F1-Score. It balances the precision and recall values and is more suitable for ratios than accuracy. The corresponding formulae of the metrics are given in Eq. 1-4.

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$$\text{Accuracy} = \frac{\text{. of correct predictions}}{\text{Total no. of predictions}} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-Score} = 2 \times \left(\frac{\text{ion} * \text{Recall}}{\text{Precision} + \text{Recall}}\right) \quad (4)$$

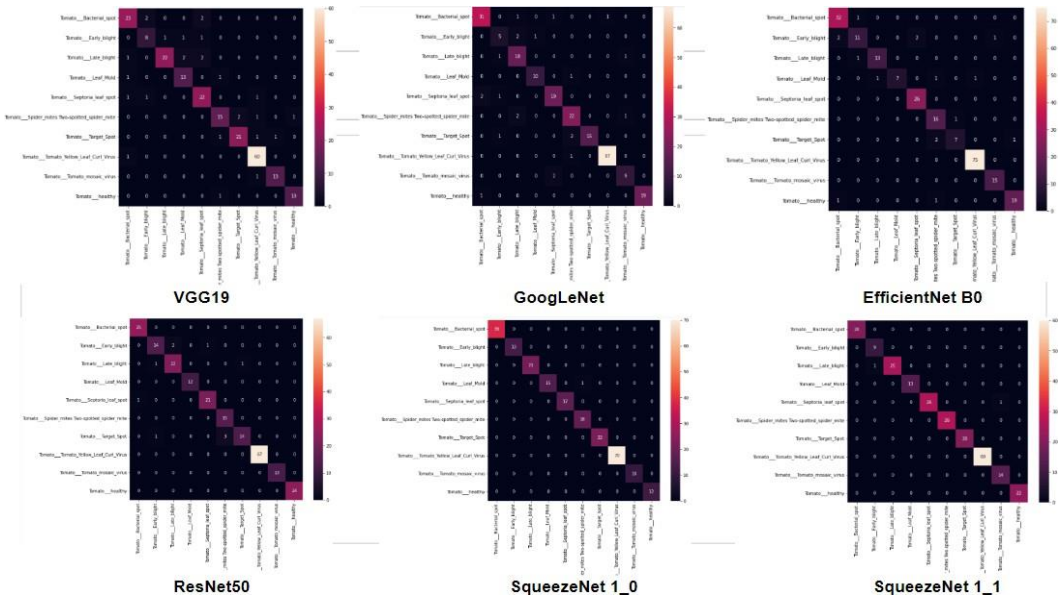

Fig. 7 Confusion matrices for different models

4. Results and Discussion

The primary motivation behind this study was to investigate the achievement of SqueezeNet deep learning architecture on the Tomato plant disease dataset and to compare the results with the other state-of-the-art deep learning models using the transfer learning approach. The performance of various models on the training dataset has been measured based on the metrics discussed in Section 3.4. The SqueezeNet as well as all other deep learning models were trained up to 25 epochs. The accuracy and loss per epoch for each model have been depicted in Fig. 8.

Fig. 9 represented the validation and test accuracy of different models. The model SqueezeNet1_0 gave the highest test accuracy of 99% among other architectures. The performance metric values for each class in the SqueezeNet1_0 model are discussed in Table

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2. VGG16 architecture performed worst on the Tomato dataset and has the lowest test accuracy of 88.4%. The SqueezeNet1_1 architecture also performed well and has the second-best test accuracy of 98.6%. The performance of all the architectures with their respective metrics is compared in Table 3.

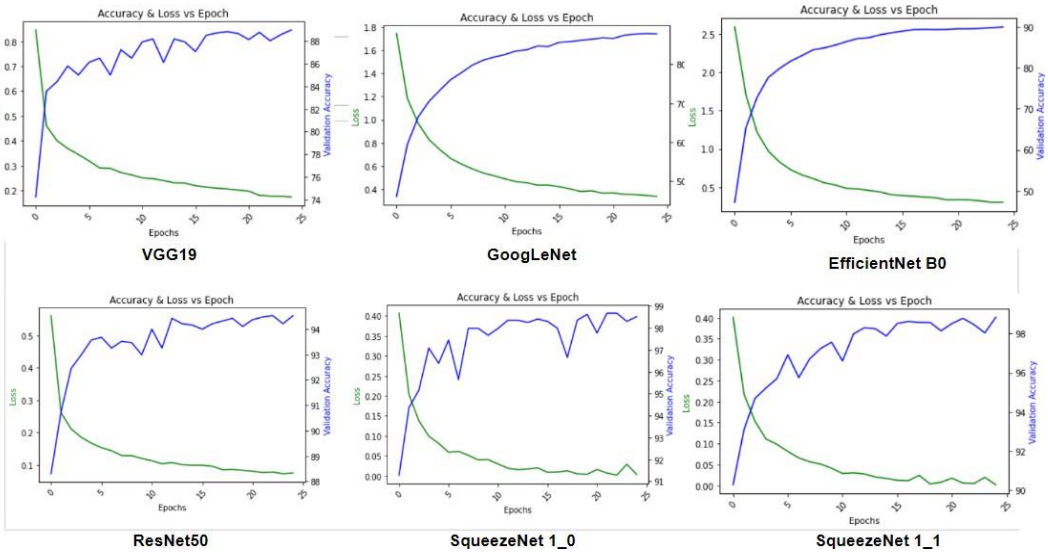

Fig. 8 Graph of Accuracy and Loss versus Epoch for different models

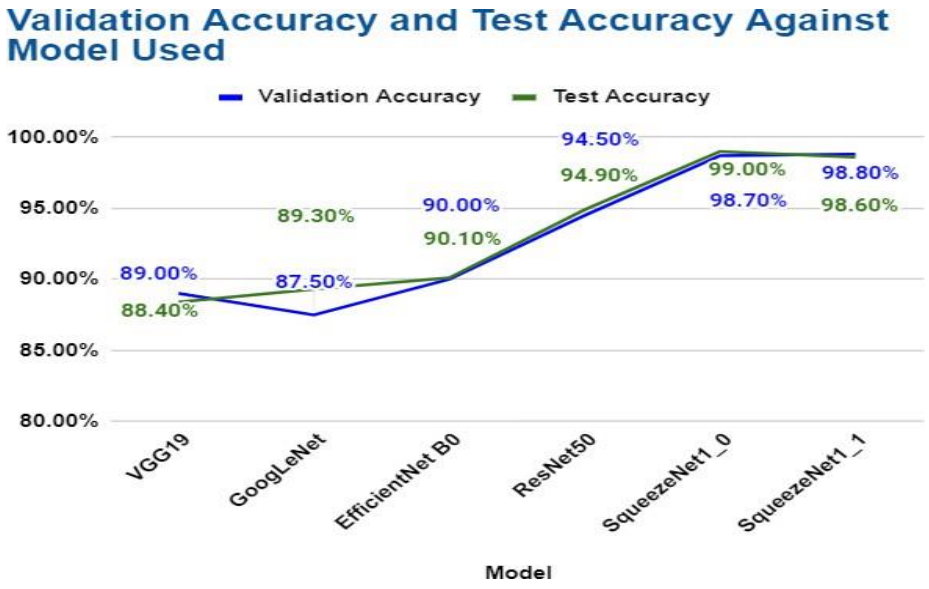

Fig. 9 Graph of Validation and Test Accuracy against different models

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Disease class	Precision	Recall	F1-score	Support
Tomato_Bacterial_spot	1.00	1.00	1.00	38
Tomato_Early_blight	1.00	1.00	1.00	13
Tomato_Late_blight	1.00	1.00	1.00	21
Tomato_Leaf_Mold	1.00	0.94	0.97	16
Tomato_Septoria_leaf_spot	1.00	1.00	1.00	17
Tomato_Spider_mites Two-spotted_spider_mite	0.95	1.00	0.97	18
Tomato_Target_Spot	1.00	1.00	1.00	22
Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	70
Tomato_mosaic_virus	1.00	1.00	1.00	10
Tomato_healthy	1.00	1.00	1.00	12
Accuracy			1.00	237
Macro Avg	0.99	0.99	0.99	237
Weighted Avg	1.00	1.00	1.00	237

Table 2 Classification Report of SqueezeNet1_0 model

Model Name	Test Accuracy	Precision	Recall	F1-Score
VGG16	88.40%	0.89	0.89	0.89
GoogLeNet	89.30%	0.91	0.91	0.91
Efficientnet B0	90.10%	0.93	0.93	0.93
ResNet50	94.90%	0.96	0.96	0.96
SqueezeNet1_0	99%	1.00	1.00	1.00
SqueezeNet1_1	98.60%	0.99	0.99	0.99

Table 3 Performance Comparison

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5. Conclusion

In this study, we present the SqueezeNet deep learning architecture as a solution for classifying tomato plant diseases using the Plant Village dataset. Our findings demonstrate that the proposed SqueezeNet models significantly outperform other state-of-the-art deep learning architectures in plant disease detection, leveraging transfer learning techniques. The SqueezeNet1_0 and SqueezeNet1_1 architectures achieved impressive test accuracies of 99% and 98.60%, respectively. Remarkably, despite having 2.4 times fewer parameters, the SqueezeNet1_1 model surpassed other convolutional neural network (CNN) models in performance. These results indicate that the SqueezeNet1_0 model, with its superior test accuracy, is particularly effective for the accurate identification of tomato plant diseases. Future research directions include expanding the dataset to incorporate a greater variety of disease types, which could further enhance the model's accuracy and applicability.

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