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Utilizing ResNet Architectures for Identification of Tomato Diseases

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ABSTRACT

In this study, the effectiveness of various deep learning models in detecting diseases in tomato leaves has been thoroughly evaluated, with a particular emphasis on the ResNet architecture family. The primary focus was on assessing the capabilities of advanced models like Res2Next50 and Res2Net50d, which have shown exceptional performance in identifying and classifying various tomato leaf diseases. The results of the study reveal that the Res2Next50 model achieved the highest accuracy rate of 99.85%, accompanied by an impressive F1 score of 99.82%. This indicates a high level of precision and robustness in distinguishing between healthy and diseased leaves. Additionally, the Res2Net50d model has also proven to be highly effective, attaining an accuracy rate of 99.78%, precision of 99.73%, and recall of 99.72%. These metrics suggest that the model is not only capable of correctly identifying diseased leaves but also has a low false positive rate, making it a reliable tool for practical applications in agriculture. When compared to other popular convolutional neural network (CNN) architectures, such as VGG16 and DenseNet121, the ResNet models, particularly Res2Next50 and Res2Net50d, have demonstrated superior performance. This highlights the strength of the ResNet family in handling complex classification tasks, especially those involving fine-grained distinctions between different types of tomato leaf diseases. The findings of this research suggest that CNN models like Res2Next50 and Res2Net50d can significantly enhance the accuracy and reliability of automated disease detection systems in agricultural settings. Such systems can provide valuable support to farmers and agricultural professionals, enabling early and accurate identification of diseases and, consequently, better crop management and productivity.

1. Introduction

Tomatoes are among the most widely cultivated and economically important crops worldwide, which can often be confused with vegetables, whereas they are considered fruits. The main reason for their popularity is their high content of nutrients, which include antioxidants that are necessary for fighting cellular damage and keeping the body healthy [1]. Environments such as open fields, greenhouses, and advanced net houses are among the various places where tomatoes are grown; tomatoes, therefore, demonstrate their adaptability and significant place in global agriculture.

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The economic significance of tomatoes is evident in their immense participation in the global vegetable market. The production of tomatoes confronted these difficulties besides the positive developments, especially the invasion by different plant diseases that can destroy the yield and quality so that the losses will be very high [2]. Tomato fields are very susceptible to various kinds of diseases, one of which is early blight and the other one is late blight. They have a reputation for being very damaging crops of high productivity [3]. These diseases are more than just crop loss; they also involve the whole agricultural economy and the farmers' livelihood, which are affected by the diseases. Conventional disease detection techniques, based on human-based inspection, are usually labor-consuming and subject to the risk of mistakes. This dependence on human know-how can cause delays in identifying and treating diseases, which further aggravates the already difficult conditions the farmers’ encounter. The recent developments in machine learning and computer vision give some creative ways to solve these problems.

Convolutional Neural Networks (CNNs) which are the most efficient artificial intelligence tools have gained a lot in virtual imaging-based plant disease diagnosis and reporting. CNN can give a complex image of a large data set and can learn from information with no need for manual features [4]. CNNs are very skilled at processing and correctly interpreting large data sets with high accuracy, which makes them perfectly matched for agricultural applications where precise and clear disease detection is very important. CNNs are very successful in health monitoring and many other applications like the classification of tomato diseases, CNNs proved their power. Recent studies highlight the significant advancements in the application of CNNs to tomato disease management. For instance, AlexNet, VGG16, GoogLeNet, and MobileNetv2 have been employed to classify various diseases affecting tomato plants, such as bacterial spots, early blight, and late blight, from the PlantVillage database [5]. It is no wonder that deep learning models are being used for disease detection with quality results. This has led to a significant reduction in the amount of manual work, as well as a faster identification of the problem. CNN-based models are undoubtedly one of the best methods for disease classification. High accuracy rates in identifying and classifying various types of diseases from leaf images have been documented [6].

The implementation of CNNs to help control tomato disease represents a major step forward in disease surveillance and management. CNNs employ large volumes of images combined with significant computational power to identify the disease symptoms at an early stage and thus assist in the treatment of the disease and prevent the spread of infections. Also, data augmentation methods offered a lot of help to evade the overfitting problem which is one of the most severe in the case of large datasets. For instance, Zhou et al. [7] suggested cross-label suppression methods for the representation of data, and Ma et al., [8] applied variational Bayesian learning methods to get flexible performance. The efficiency of data augmentation is evidenced by the increasing precision rates, with augmentation getting 75.85% accuracy [9]. Hidayatuloh et al. used SqueezeNet to classify tomato plant diseases and getting a result of 86.92% accuracy [10]. Khamparia et al. utilized CNN networks like InceptionV3, VGG19, SqueezeNet, and ResNet50 for the classification of cervical cells in cervical cancer [11]. Ayu et al. used MobileNetv2 for the classification of cassava plant disease, getting 65.6% accuracy [12]. Kunduracioglu & Pacal, provided 100% accuracy on diseases of grape leaves with CNNs and Vision Transformers (ViT) [6].

In addition to disease management, the integration of robotics and automation in agriculture holds significant promise for enhancing productivity. Lettuce picking, monotonous as it may be, is a perfect example of the robotic automation potential. Robotic technologies are, however, on the rise[13], and problems of fruit detection and classification still exist. Traditional robotic systems ought to operate in a sequence of dangerous and neural environments where, at times, the size, color, or ripeness of the fruits may be invisible or can change unexpectedly [14], [15]. Object tracking and classification such as YOLO and SSD will be needed in the near real-time processing flow for agribusiness [16]. These methods not only help harvests run more smoothly but also solve the problem of labor shortages and the increasingly high costs of operations [17]. Above, the combination of deep learning and robotics in agriculture represents a bright future for the management of crop diseases and the improvement of harvesting efficiency. The agriculture sector, by using advanced image processing techniques and automated systems, can, thus, overcome the current challenges and achieve higher productivity and sustainability. The study proposes to help develop more effective methods for managing plant diseases and advancing agricultural technology that will, in the end, support the sector's growth and resilience.

1.1 Literature Review

The classification of plant diseases has emerged as a significant research area in the agricultural industry. Deep learning and image-processing techniques are effective in this area through recent studies. This literature review will consider how applicable and effective different methods and models are. Convolutional Neural Networks (CNN) have been tremendously helpful in the diagnosis and classification of plant diseases. Undoubtedly, the CNN architectures and models like AlexNet, GoogLeNet, VGG, and DenseNet used in deep learning and computer vision have turned deep learning into the spotlight. The models are very deep and use nonlinear activation functions to be trained to be very good at distinguishing the information. To illustrate, brain tumors and grape plants can be accurately classified with the use of AlexNet and VGG16 [18], [19]. Also, Jeon & Rhee proposed using AlexNet and VGG16 for disease classification and these models were tried on several datasets [20]. Deep learning models require substantial financial support, prolonged training time, and a considerable amount of other resources. The picture of oversaturation, especially when it comes to the presence of a diverse type of data, can be generalized as a very big problem to tackle [21]. In this aspect, the data-enriching methods are the basic instruments of steering. For instance, Zhou et al. [7] wanted to use cross-labels to decrease the influence of data representations, while Ma et al. [22] successfully showed flexibility by applying variational Bayesian learning techniques to achieve the predictive distribution of inputs.

Toğaçar et al. used two different models, AlexNet and VGG16, for the diagnosis of brain tumors [23]. Lenz et al. confirmed the use of deep learning methods with AlexNet, GoogLeNet, and Inception models in the classification of the adhesion strength that was almost similar to the human assessment with a classification accuracy of 85% to 90% [24]. Rehman et al. made use of transfer learning for brain tumor classification with the help of VGG16, AlexNet, and GoogLeNet models, and the VGG16 model gave an accuracy of 98.69% which was the highest among them [25]. Pereira et al. taught AlexNet how to classify grape vines, and the classifier achieved an accuracy of 77.30% on the test model and then improved it to 89.75% with the Flavia dataset [26]. Türkoğlu & Hanbay, used transfer learning with AlexNet on a self-collected dataset and checked the performance parameters of their model [27]. Liu et al. applied AlexNet, GoogLeNet, and VGG16 models for the classification of apple diseases from a self-collected dataset in China [28]. Lu et al. utilized VGG16 and MobileNet deep learning models for the discrimination of Alzheimer's disease using MRI images [29]. KC et al. advocated the MobileNet model due to its satisfaction with the accuracy and small size for real-time crop diagnosis over the VGG16 model [30]. The deep learning networks' dataset augmentation reached a precision rate of 75.85% [9].

Huang et al. did the segmentation of tomatoes and found these approaches to be effective [31]. Besides that, Arum Sari et al. classified tomatoes into 6 classes of groups using two channels from the YCbCr and YUV color spaces [32]. Therefore, the fruit and plant diseases color-based methods have a deiced advantage in the recognition of disease of fruits and plants. The deep learning method has gained tremendous progress in object detection and classification tasks. Single-stage detection frameworks such as YOLO and SSD are fast and efficient for object detection and classification [33]. YOLO models are capable of achieving accurate results despite variations in environmental conditions. Chen et al. [34] and Zhang et al. [35] are among those who have improved the YOLOv3 model, while Xu et al. [36] improved the YOLOv3 Tiny model. Liu et al. [37] enhanced the YOLOv3 Tiny model, and Lawal [38] achieved successful results in tomato detection by integrating different activation functions.

Data augmentation is a necessary action that results in the better functionality of deep learning models. Different data augmentation strategies are used, in particular, to discourage overfitting. Munoz-Bulnes et al. implemented two data augmentation strategies for road detection, namely, geometric transformations and pixel value changes [39]. These techniques are ways by which the model can perform better and thereby become more successful. Ma et al. provided real-time, flexible solutions for a range of applications through the application of different data support techniques [8].

CNNs and deep learning frameworks have gained ground against plant disease detection and classification. The breakthroughs that have taken place in this area can greatly help in increasing agricultural productivity and decreasing the negative effects of diseases on the environment. Data augmentation techniques are very useful in improving the performance of deep learning models and the application of deep learning techniques in general.

2. Methodology

2.1 Dataset and Preprocessing

The PlantVillage dataset has played a significant part in helping us know plant disease classification very well. Our research was focused specifically on the tomato diseases. The dataset comprises multiple classes of tomatoes, such as healthy tomatoes and those infested with diseases like bacterial spot, early blight, and late blight (Fig.1). Each class contains enough images that direct the training of deep learning models to achieve high accuracy in identifying and classifying the tomato diseases.

Fig.1 Examples of tomato classes from PlantVillage dataset

Table.1
Tomato classes and values from dataset

Class Names	Total(100%)	Train(70%)	Validation(15%)	Test(15%)
Bacterial spot	2127	1489	319	319
Early blight	1000	700	150	150
Healthy	1591	1114	238	239
Late blight	1909	1336	286	287
Leaf mold	952	666	143	143
Mosaic virus	373	261	56	56
Septoria leaf spot	1771	1240	265	266
Spider mites	1676	1173	251	252
Target spot	1404	983	210	211
Yellow leaf curl virus	5357	3749	804	804

Table 1 gives a complete report on how the images of tomato diseases and the healthy are divided into the training, validation, and test sets. The dataset is divided into training (70%), validation (15%), and test (15%) subsets for each class, where the balanced approach is the goal for model evaluation. On the one hand, the training subset is large enough to allow in-depth learning. On the other hand, the validation and test subsets are precisely balanced in order to gauge the model's capability to generalize. By the way, the dataset is small, with a total of 13,875 tomato images. The distribution shows a great imbalance, with 5,357 images for the Yellow leaf curl virus and only 373 images for the Mosaic virus. Boosting the performance of the models being trained on small datasets as well as making the results more realistic and aligned with real-world situations are the benefits of data augmentation methods. Data augmentation is a method that helps a model learn to be more robust by being able to adapt to different conditions which in turn results in more accurate and generalized results.

2.1.1 Data Augmentation

Data augmentation gathers information through composite methods and generates new samples for training. This is done by methods such as generating new visual samples by rotation, flipping, and scaling, cropping, and changing color (rotation, flipping, scaling, cropping, and color adjustments). The augmentation of data helps by providing all these different forms of guidance, in turn, data helps to increase the generalization ability of the model and help it to work well in situations that are never seen. It is a means through which one can effectively cure overfitting, the stage when a model becomes an expert on particular data, but fails to learn to generalize from it. By data augmentation, the model is now able to experience a wider range of possible scenarios and conditions as a result of this, thus, better robustness as well as the accuracy of the model is improved. This technique is particularly valuable in scenarios were acquiring a large amount of labeled data is challenging or expensive, as it allows for the creation of a more comprehensive and diverse training set from a limited number of original samples.

2.2 Deep Learning

Deep learning is the most recent technology in teaching computers to learn by themselves and is a development from the simple neural networks (ANNs) to the more complex CNNs [40]. When the first ANN was used, the feature extraction and selection were manually done. However, in the case of CNNs, feature extraction was one of the steps of the network, which then filtered through the architecture of the network. This step propelled CNNs to the next level of feature auto-extraction, thus, it made deep learning so potent for tasks like image recognition and classification [41].

2.3 CNN

Convolutional Neural Networks (CNN) are neural networks that are specialized for working with two-dimensional images. CNNs, whose design is influenced by the human brain, make use of a hierarchical architecture to find out and understand the features of an image. They consist of convolutional layers that apply filters to extract features, pooling layers that reduce dimensionality, and fully connected layers for classification [6].

CNNs have proven their ability to either give accuracy on images regardless of shifting, rotation, or scaling and to analyze spatial hierarchies of pixels. With the help of local receptive fields, CNNs are easily capable of detecting key features such as edges and textures. This design not only accomplishes higher accuracy but also leads to a reduction of the hyperparameters that stimulate the training process. Moreover, CNNs can be applied in image recognition as well as object detection areas; hence their importance in a machine learning system is undeniable [42].

2.3.1 Transfer Learning

Transfer learning is a good machine learning technique bettering the use of the models which have another task. These already trained models are then used for new tasks making the latter more efficient with or without big data. Neural networks turn out to be mainly built from scratch. However, this is time-consuming and data-intensive. The fact that transfer learning is utilizing the model that is already learned on the large datasets like ImageNet does not stop it. The EfficientNet and DenseNet models can start with the weights that were learned from large-scale image datasets and after that they can be trained in the tasks that they have to do, for example, they can be used to identify apple leaf diseases [43].

The method speeds up training and improves feature extraction by using the pre-trained models with learned features that are easily transferred to new tasks. The second step is to transfer the model's weights to a small, domain specific dataset. The dataset is usually separated into three partitions: training, validation, and test. The training set is where the model is being made better to fit the parameters, and the validation set is used to compare results and learn hyperparameters such as learning rates and dropout rates to add. The basic technique such as stochastic gradient descent (SGD) and Adam can then be used to modify the model. Hyperparameter tuning, which is mainly carried out by grid search and Bayesian optimization, also enables the models' performance by a more comprehensive search through configurations.

2.3.2 ResNet

ResNet (Residual Networks) was very popularized by He et al. and this is a landmark achievement [44]. ResNet solved the problem of vanishing gradients in deep networks when they came up with a new method that was based on residual connections combined with residual blocks. These connections provide a way for the rest residual (or sometimes we call it) error to pass smoothly through all the layers so that the training can be more stable and deeper. networks can be trained more effectively. In the ResNet series, ResNet-34, ResNet-50, and ResNet-101 are three of the well-known versions, mainly due to their increased depth and complexity. To begin with, ResNet-34, which is the starting model of ResNet, has 34 layers. To be more specific, it involves 3x3 convolutional and the basic constituents of residual blocks, thus, it is a compromise between deep learning and computational resources [44].

ResNet-50 extends this framework to 50 layers and introduces bottleneck blocks. These blocks lessen the width of each residual block, thus, the computational load, however, they improve the model's efficiency and accuracy. Hence, ResNet-50 can be used to obtain both high accuracy and short training times. ResNet-101 ups the scale of the architecture to 101 layers, which results in the model being capable of recognizing more complex and abstract features. Although this deeper model has the potential to outperform larger datasets, it also needs more computational resources. All ResNet architectures give more depth and complexity to the learning process resulting in better success on the more difficult tasks. The ResNet family has been embraced widely in deep learning, and it has been demonstrated that they are very capable of handling many different tasks.

2.3.3 ResNeXt

ResNeXt which came from the research work of Xie et al. is a practical advancement in the CNN architecture as it is use of cardinality which is the number of parallel pathways or branches that are there in each residual block [45]. ResNeXt is a modification of the ResNet architecture, where it replaces the ordinary residual blocks with cardinality blocks that are composed of several convolutional branches[46]. Each branch in a cardinality block has its filters, and all branches are combined and then sent to the next layer [47], [48].

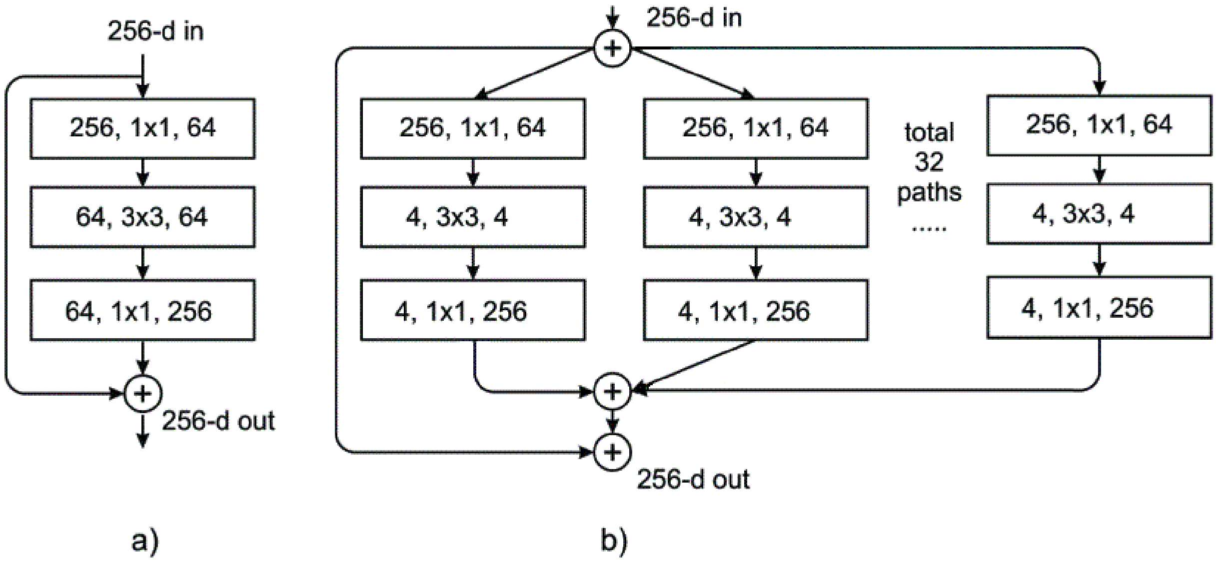

Fig.2 Architecture of ResNext [45]

The block's cardinality, which is a hyperparameter, determines the number of parallel branches, which consequently, produces a complex feature extraction process that is more flexible. By which means, the learning capacity of the model is improved to allow it to capture varying and complicated features while remaining efficient in its processing. ResNeXt outperformed with regard to image classification tasks in various datasets, such as ImageNet, CIFAR-10 and CIFAR-100, pushing the state-of-the-art boundaries with the use of much fewer parameters compared to other deep neural networks [45].

3. Results and Discussion

In this study, a performance evaluation of various deep-learning models used for detecting diseases in tomato leaves is presented. Historically, data processing has often depended on methods like training-test or training-validation splits. However, these strategies may not sufficiently demonstrate the models' abilities to handle unseen data. Unlike previous studies, our method employed a training-validation-test split, ensuring that the datasets were randomly allocated into separate training, validation, and test sets. Consequently, each model was evaluated exclusively on its performance with the unseen test set, enabling an accurate assessment of its generalization capabilities. Each model went through a single training cycle, and the model that performed best was chosen based on validation metrics. This selected model was then rigorously evaluated on the test data to assess its performance on previously unobserved samples.

The models are analyzed based on standard metrics such as accuracy, precision, recall, and F1 score to determine the most efficient model. In addition to models from the ResNet family, other architectures such as VGG16 and DenseNet121 are compared, highlighting the strengths and weaknesses of each approach. Table 2 summarizes the key performance indicators of the tested models.

Table 2.
Performance metrics of ResNet models and other CNN models for identification of tomato diseases

Model	**Accuracy%**	**Precision%**	**Recall%**	**F1-Score%**
ResNet18	99.49	99.32	99.41	99.36
ResNet34	99.45	99.22	99.26	99.24
ResNet50	99.38	99.20	99.30	99.24
ResNet101	99.56	99.42	99.44	99.42
ResNet152	99.67	99.59	99.57	99.58
Res2Next50	**99.85**	**99.84**	**99.81**	**99.82**
Res2Net50d	99.78	99.73	99.72	99.73
VGG16	99.60	99.51	99.57	99.53
DenseNet121	99.63	99.51	99.53	99.52

As seen in Table 2, in terms of accuracy, Res2Net50d (99.78%) and Res2Next50 (99.85%) stand out as the models with the highest accuracy. This data shows that each model is very competent in creating accurate forecasts for the detection of diseases. It is noteworthy that Res2Next50 has slightly increased accuracy in comparison to others, putting it in a position as a reliable model for this application. By the precision evaluation criteria, the Res2Next50 (99.84%) and Res2Net50d (99.73%) models demonstrate the best performance. This implies that the overwhelming majority of diseased leaves classified as positive by these models are, in fact, diseased. These two models have low false positive rates, which implies they are remarkably sensitive to the avoidance of false alarms. Res2Next50 (99.81%) and Res2Net50d (99.72%) highlight themselves significantly in regard to recall. The high recall rates indicate the effectiveness they have in recognizing diseased leaves. Missing diseased plants is essential to highlighting the importance of and especially applies to fields like agriculture. The F1 Score performs a general evaluation of performance through the combination of precision and recall metrics. Res2Next50 and Res2Net50d stand as the models that achieve the greatest values for F1 Score with 99.82% and 99.73%, respectively. The indication is that both models achieve balanced and effective results, implying their overall performance is very satisfactory (Fig. 3).

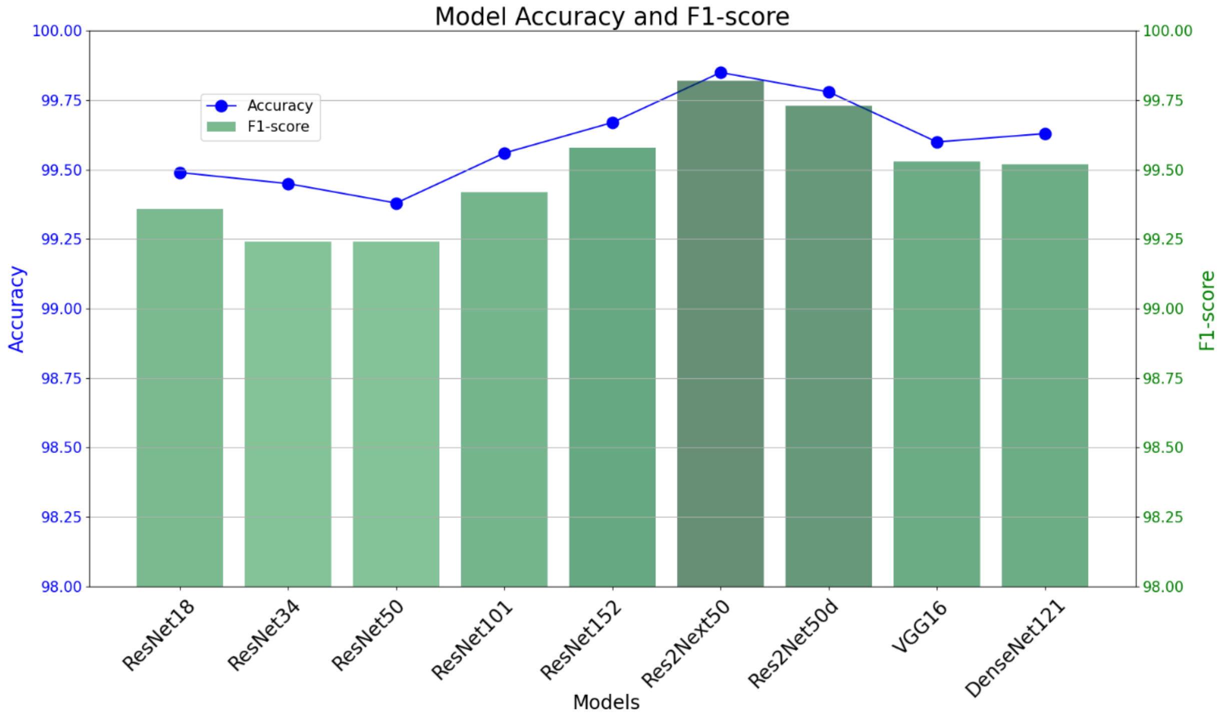

Fig. 3 Models' accuracy and F1-score

Strictly evaluating a model's performance insists on the metrics Accuracy and F1-Score. The correctness of a model's predictions, regarding overall efficacy, is measured as the proportion of correctly classified cases to the entire set of cases. In the case of a class imbalance, accuracy can be deceptive by itself. Paying absolute attention to accuracy might not sufficiently reflect the operational characteristics of the model, notably in datasets with an imbalance. In opposition, F1-Score resolves the conflict between precision and recall, and is notably effective in these kinds of situations. The metric before us, precision, highlights the rate of true positives from those identified as such, while recall highlights the performance of the model in correctly determining true positive instances. Measuring its effectiveness in finding positive cases and managing false positives is the role of F1-Score. As a result, the combination of precision along with the F1-Score gives a more nuanced assessment of model performance, along with its accurate relationship between precision and recall. In Fig. 4, you will find the confusion matrix for the Res2Next50 architecture, which excels in performance metrics.

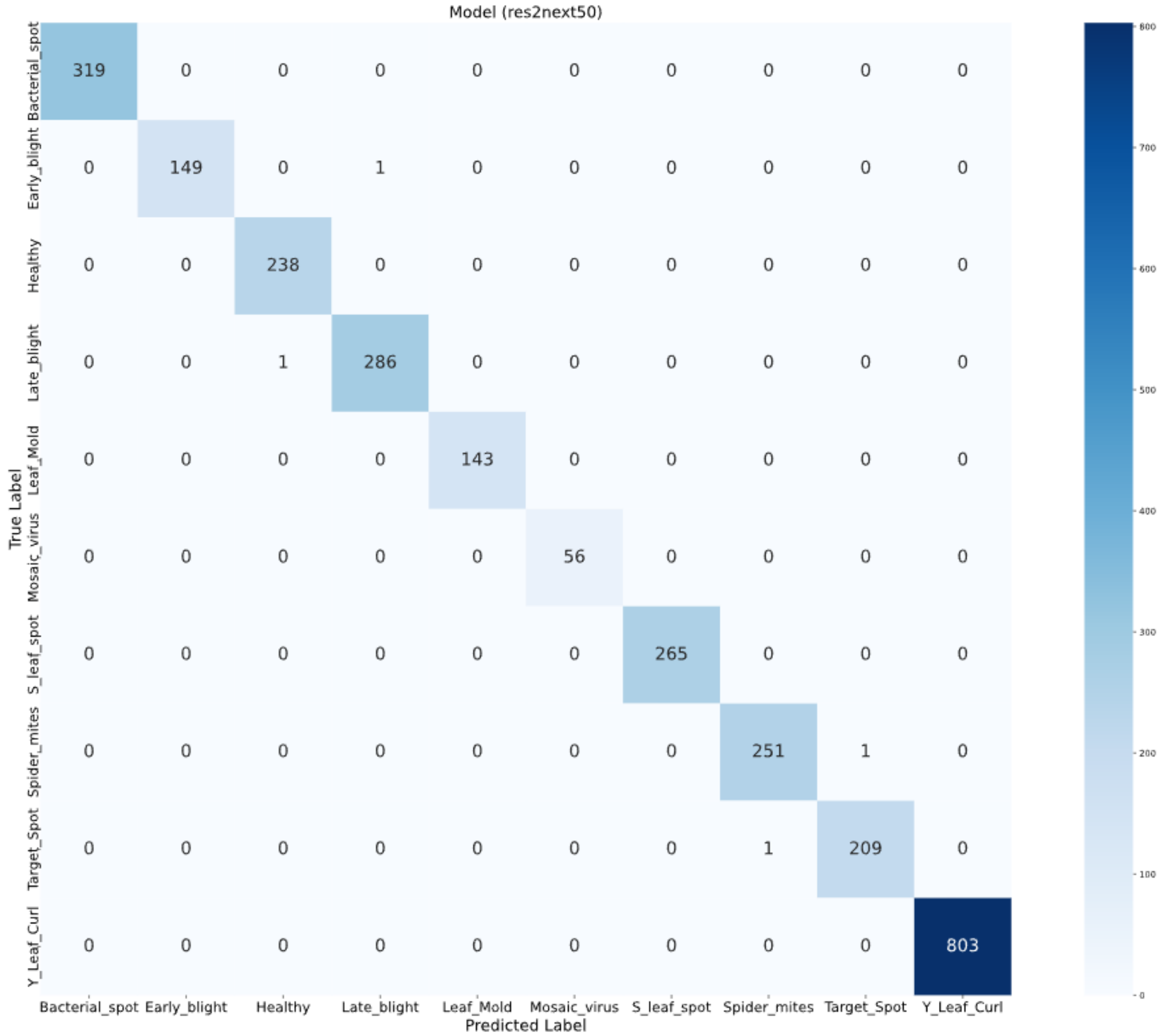

Fig. 4 Confusion matrix for Res2Next50

Res2Next50 is a model that shines by achieving the top scores in all measurable metrics. Because of its highest values related to accuracy, precision, and recall, it is an outstanding option for the detection of diseases. In terms of overall performance, ResNet152, from the standard ResNet family, ranks next to Res2Next50 but falls a bit behind. The networks ResNet18, ResNet34, ResNet50, and ResNet101 perform effectively, but they do not measure up to the deeper network models. The outputs from VGG16 and DenseNet121 are commendable, but they do not match the performance of the Res2Next50 and Res2Net50d. The findings indicate clearly the performance of deep learning models in identifying diseases in tomato leaves and demonstrate which models outperform the rest in this endeavor.

4. Conclusion

The evaluation of the ResNet architecture family's performance in identifying diseases in tomato leaves has been thoroughly carried out in this study. Analysis of the results shows that the Res2Next50 model outperforms others, reaching a 99.85% accuracy level. The presented model delivers the optimal combination of high accuracy and an F1 score of 99.82% when compared to the other options. Also, the Res2Net50d model has successfully shown its capability with an accuracy rate of 99.78%, in addition to a high precision rating of 99.73% and a recall of 99.72%. The findings from additional ResNet models, especially ResNet152 and ResNet101, prove to be remarkable because they have obtained an accuracy of 99.67% and 99.56% respectively. The analysis illustrates that VGG16 and DenseNet121 models obtained good accuracy rates; however, Res2Next50 and Res2Net50d usually perform better in comparison. Ultimately, this study concludes that the Res2Next50 and Res2Net50d models effectively identify diseases in tomato leaves and deliver a trustworthy solution for this area. The directions for further research are to apply these models to more various and extensive data to check the models' validity in other environmental contexts and with other diseases. However, additional work focusing on the interaction of these models with real-time monitoring systems and future use of mobile applications may reveal even more potential for the development of these models for disease management and precision agriculture.

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