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Effectiveness Of Pre-Trained Deep Learning Models In Smart Agriculture For Leaf Disease Detection

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Abstract: *With major crop losses and jeopardising food security, tomato diseases seriously confront world agriculture. Reducing the economic and environmental consequences of these illnesses depends on fast and accurate diagnosis of them. This work investigates the use of deep learning method known as transfer learning to enhance tomato leaf disease diagnosis. Transfer learning, a technique in deep learning, allows models to leverage pre-trained knowledge on similar tasks, improving performance and reducing the need for large datasets. This method has gained popularity in agricultural disease detection due to its efficiency and adaptability across different domains We investigate many pre-trained models including AlexNet, DenseNet, ResNet18, VGG16, VGG19, and InceptionV3 in their ability to identify certain tomato illness. Key performance measures including accuracy, precision, recall, computational efficiency, and resource consumption guide evaluation of the models. AlexNet has the greatest overall performance, according to the results, which mix accuracy with computational economy to make it particularly appropriate for settings with low resources. Conversely, deeper models like ResNet18 and VGG16 need large processing effort but have better accuracy. These results show that transfer learning may be a powerful tool for better agricultural disease diagnosis, which can lead to better crop management methods, more accurate disease detection in tomato leaves, and ultimately, more food security and more sustainable farming.*
Keywords: *Tomato Leaf Disease, Ai, Transfer learning, ResNet, VGG, Inception, MobileNet, Sustainable Agriculture.*

1. INTRODUCTION

Feeding millions of people and greatly helping to maintain the economic stability of agricultural areas all throughout the globe, tomato plants are vital for world agriculture. Essential in both subsistence and commercial cultivation, tomatoes are a food staple and a main component in many recipes. Growing tomatoes does, however, present unique difficulties; the most important one being the possibility of illness. Caused by bacteria, fungus, viruses, and pests, these diseases might destroy crops, thereby affecting decreased yields, poor-quality product, and significant financial losses for farmers and the agricultural industry [1,5]. Tomato is a rich source of Vitamin C, E, Potassium and beta-carotene. The high cost or limited availability of tomatoes can affect the cost of diet of an individual. Tomato production is a critical concern for any agricultural industry and its product affects the food and other industries.Disease detection has relied on farmers or agricultural consultants physically looking over tomato plants[6,9]. Although this method has been basic in controlling illnesses in agriculture, it has some clear disadvantages. X`Manual examinations need great effort and comprehensive study of large areas. Particularly in places with low resources, the labour-intensive procedure calls for a trained personnel that might be difficult to obtain [3,11]. Furthermore prone to human mistake is the visual indication of plant illnesses, which could be faint, overlapping, or readily misread depending on the surroundings. These problems emphasise how urgently new precise, scalable, and efficient techniques for tomato plant disease detection are needed. New chances to address these issues have now come from technical developments.Deep learning is one obvious advance that has revolutionised picture categorisation, pattern recognition, and decision-making among other fields. Deep learning, a subfield of artificial intelligence, is skilled at analysing vast amounts of data to find trends and provide forecasts. Its use in agriculture for plant disease detection which has attracted a lot of interest. Deep learning algorithms can precisely diagnose illnesses by analysing pictures of plant leaves, usually surpassing human ability [10,21].

Transfer learning has become transforming method in area of DL. It addresses certain problems with little further training using pre-trained models created on large datasets from several fields. In agriculture, compiling large labelled datasets of damaged plant photos may be costly and challenging or both, this approach is very helpful. It eliminates demand for large datasets, lowers training time, and lowers computing resource requirements by using pre-trained models, therefore providing a great alternative for building disease detection systems for tomato plants. This work investigates how transfer learning may be used to detect illnesses in tomato leaves. It evaluates ResNet, VGG, Inception, and MobileNet among other pre-trained models to see how well they identify tomato plant illnesses. Every type suits different circumstances as they have unique architectural elements and advantages. By means of a methodical evaluation of their performance, the work aims to identify the most exact and economical model for tomato disease detection. This study has important ramifications. Disease detection may provide farmers precise so they may respond with purpose. This not only increases crop yields but also lessens dependence on too heavy pesticide usage, therefore encouraging sustainable agricultural methods. For farmers worldwide, these technologies may also be included into mobile applications, drones, or agricultural robots providing scalable answers. Although tomato plants are still at danger from continuous disease threats, they are very vital for world food security and economic stability. Conventional disease detection techniques fall short for the demands of contemporary agriculture [7, 23]. One exciting answer is using cutting-edge technology like transfer learning. Using pre-trained deep learning models will help us to develop scalable, accurate, and effective techniques for tomato leaf disease detection, therefore strengthening and ensuring a sustainable agricultural future. DL has lately evolved as a revolutionary technique in agricultural technology, particularly for plant disease detection. Innovative ideas that may effectively and precisely detect and diagnose these problems early on are desperately needed given the growing worldwide demand for food and the growing difficulties with pests and illnesses. Often based on visual assessments by qualified professionals, conventional methods of illness diagnosis might be slow, labour-intensive, and prone to human mistake [2,19]. The raw image is captured from a farm. These images are acquired using a fixed camera that captures the photos at a specific time. Convolutional Neural Network (CNN) is the most promising deep learning model that can process image data effectively. [27,28]. For any analysis, there is a requirement fora larger imageset. The captured images can be infected and disrupted by the environmental, camera quality and focusing factors To overcome these challenges, several studies have looked at automatically identifying plant diseases using deep learning, particularly CNNs. CNNs have demonstrated amazing capacity to recognise patterns and detect diseases across numerous crops, intended for picture recognition. Researchers have found diseases in several agricultural products like tomatoes, rice, and wheat using CNNs. By means of training on vast-scale image datasets, these algorithms grasp the salient features differentiating healthy from diseased plant tissues. Early disease identification is possible using CNNs because, after training, they can effectively categorise fresh pictures of plant parts such as leaves, stems, or fruits. The tomato farming can be affected by various diseases that can be caused because of various dominating factors. These diseases can cause significant productivity and quality losses. [29,30] Transfer learning is one of the most intriguing advancements in deep learning for detecting plant diseases. The method relies on fine-tuning a model that has already been trained on a massive dataset, and it often hails from a related subject. When it comes to plant diseases, for example, large amounts of tagged data might be hard to come by or expensive to collect. This solution drastically reduces that requirement. The second benefit is that the training process is accelerated since the model already has generic properties that are applicable to the present project. Finally, because it lowers the computer resources needed to train deep learning models from the ground up, transfer learning makes more sense in real-world agricultural environments especially in areas with limited resources [8,10].

Though significant challenges still need to be solved, deep learning has made remarkable progress. One of the challenges are complexity of agricultural data. Usually including a broad images varied in ambient conditions, lighting, background, and disease indications, plant disease databases. Deep learning models find it more challenging to effectively span multiple environments due to this variance. Furthermore difficult for us is balancing computational economy with accuracy. Some models have considerable computational cost, hence even if they are very accurate, they may not be appropriate for use in settings with restricted resources. Models optimised for sacrifice accuracy, therefore lowering the performance in real-world environments. Deep learning-based disease detection in pragmatic settings calls for resolving the trade-off between accuracy and efficiency. Another challenge is models' capacity to stretch to real-world events. They usually suffer in changing environments, even if they could shine on carefully chosen data. Variations in plant varieties, disease development, and climate conditions might generate training data and real-world scenario gaps compromising performance. Therefore, models have to be able to change with the times as successful agricultural applications rely on them. Six pre-trained deep learning models for tomato leaf diseases will be compared in this study in order to solve these challenges [19,25]. Specifically, the project aims to determine the most efficient model for tomato plant disease recognition by evaluating models based by large-scale data. We take a look at six models from the most popular and extensively used architectures in the deep learning space and compare them. All of the models are great candidates for this study given their unique set of advantages, which include more effective networks, more efficient parameter utilisation, and varying degrees of computational complexity. The aim of this work is to identify the pre-trained model with optimal computational economy/accuracy balance [20] able to diagnosis tomato leaf diseases. By means of an analysis of a collection of tomato plant images, this work aims to provide perceptive assessment of the best deep learning techniques for plant disease diagnosis. The results of this work might guide further initiatives aiming at creating strong, efficient, scalable disease detection systems fit for use in real-world agricultural environments, therefore helping farmers in early disease identification and increasing crop yields. The use of deep learning techniques, such as transfer learning, has great promise for enhancing plant disease detection in general. Though automation of this process has advanced, issues like dataset complexity, model generalisation, and the balance between accuracy and efficiency remain [6,13]. Six pre-trained models will be compared in this work to identify best one for tomato leaf disease detection, therefore addressing these difficulties. Among the increasing difficulties presented by plant diseases, the findings might greatly affect agricultural methods and support food security.

2. METHODOLOGY

Along with samples from healthy leaves, the dataset used in this work include photos of tomato leaves affected by many illnesses, including bacterial spot, early blight, and leaf mould. Pre-processing, normalising pixel values and enriching the dataset using techniques, helps to enhance picture quality. There are 18,160 photos in the dataset of the research split into four separate groups. Healthy; bacterial spot; early blight; leaf mould; to guarantee complete model assessment, data was divided into training (80%) and testing (20%). Several augmentation methods were used to improve generalising power of model and raise variety of the dataset. These methods call for random cropping and zooming with rotations between 0 and 45 degrees. Such augmentations enhance the training process and replicate real-world variability thereby enabling the models to perform effectively in a range of circumstances [4,14,22].

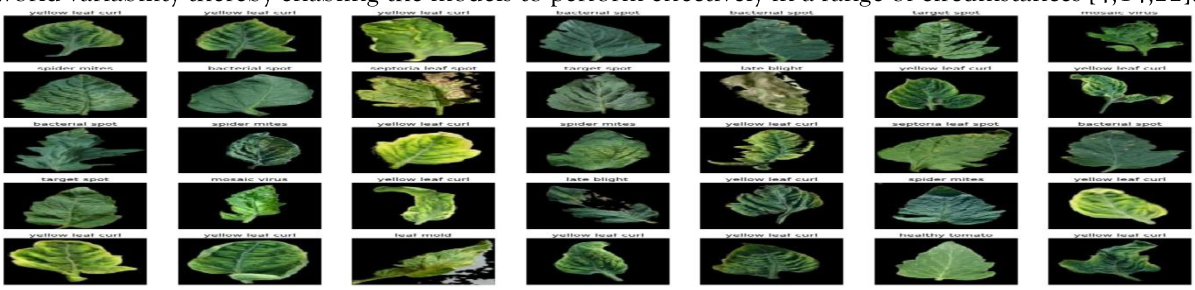

Figure. 1. Tomato Leaf Images

3. TRANSFER LEARNING MODELS

Six pre-trained models, each with unique strengths, were selected to evaluate tomato leaf disease detection. Although it is a shallow model, AlexNet's computational efficiency allows it to train and infer quicker than other models. The vanishing gradient issue may be addressed by the deep residual network ResNet18, which allows for the building of deeper models. The VGG16 and VGG19 models both have similar design and are famously good in image classification. The feature propagation is enhanced by denseNet since each layer is connected to different layer. With its combination of convolutional layers of different sizes, InceptionV3 can now handle picture categorisation tasks with ease. These models were chosen based on their shown performance in many picture recognition challenges and their possibility for transfer learning in the field of leaf disease diagnosis [15, 22].

4. EXPERIMENTAL SETUP

Using a dataset of tomato leaves, pre-trained models are refined to improve their disease detecting capability. For every model, several hyperparameters are carefully changed throughout this process to get best outcomes. The goal of setting the learning rate is to ensure that the model converges quickly enough without going too far from the best possible solution. The batch size, which indicates the number of data processed before updating the parameters, is selected in order to strike a compromise between training speed and stability. To avoid overfitting during training, it is important to choose an appropriate number of epochs, or total sweeps over the dataset. A stratified dataset is used for training and testing purposes, with the goal of evaluating the models in scenarios that mimic the actual distribution of tomato leaf diseases. Ensuring equal representation of every class helps the model to correctly recognise all illness types, therefore preventing biases against any one class. Together with the stratified split, this fine-tuning approach guarantees robust and consistent performance in tomato leaf disease detection and helps maximise model parameters [12,16].

5. EVALUATION METRICS

Several significant criteria are used in evaluation of the models to guarantee an all-around assessment. Accuracy shows the proportion of accurate predictions the model generates, therefore reflecting the general categorisation performance. Calculating precision as ratio of real positive predictions to overall count of positive predictions helps one to understand the actual amount of the expected positive events. Emphasising the model's capacity to precisely identify all relevant situations, recall measures ratio of correct positive predictions to the actual positive cases [17,24]. The F1-score provides a balanced evaluation of the model's performance, particularly with imbalanced datasets. It is calculated as the harmonic mean of the model's accuracy and recall. Finally, the model's practicality is assessed by measuring its computational efficiency in relation to training time and resource utilisation. Indicators taken together provide good assessment of how well the models identify tomato leaf diseases. Effective Optimization methods were applied for extracting the features. The lightweight classifier reduced the complexity

6. RESULTS AND DISCUSSION

Six pre-trained deep learning models have their quantitative findings compiled in Table 1 shown here. Every model was assessed against criteria including training duration, accuracy parameters.

Table 1.Quantitative results of the study

Models	Accuracy	Precision	Recall	F1-Score	Training Time Taken (sec)
AlexNet	94.5%	0.95	0.94	0.94	121
ResNet18	93.8%	0.94	0.94	0.94	209
VGG16	92.6%	0.93	0.93	0.93	302
VGG19	90.3%	0.92	0.91	0.91	339
DenseNet	91.8%	0.92	0.92	0.92	281
InceptionV3	89.5%	0.91	0.91	0.91	321

7. CONFUSION MATRIX ANALYSIS

Important new perspectives on how successfully AlexNet and ResNet18 recognise sick and healthy tomato leaves come from the confusion matrices for both models. AlexNet showed a great capacity to distinguish between the two groups by effectively spotting 4,120 true negatives (healthy leaves) and 3,426 true positives (diseased leaves). It also included 354 misclassifications, in which sick leaves were wrongly identified as either healthy or the opposite of that. ResNet18 had similar results, with 3,400 true positives and 4,115 true negatives, proving that it could detect both types of leaves. The much higher misclassification count of 370 for ResNet18 suggests that it is not quite as good at distinguishing between the classes.

8. OBSERVATION

AlexNet is wonderful choice considering restricted resources because it stands out for its outstanding computational economy and accuracy. Its great performance to efficiency ratio guarantees reliable outcomes with reduced hardware or CPU power usage. ResNet18 preserves constant performance, which results in an acceptable mix of recall and accuracy even if it is substantially less efficient. It is very appropriate for professions needing disease diagnosis as it is essential to properly identify both sick and healthy leaves. VGG16 and VGG19 are inappropriate for environments with limited hardware even if they provide great accuracy as they are resource-intensive. Although they excel at classification tasks, their high resource demands make them inappropriate for deployment in such a real-time environment. DenseNet and InceptionV3 provide only meagre accuracy while both struggle with efficiency. Their high processing demands may make them difficult to use in environments limited in resources even if they can identify complex traits for illness diagnosis. AlexNet is largely renowned for its general efficiency; rival models provide better accuracy but at rising processing demand.

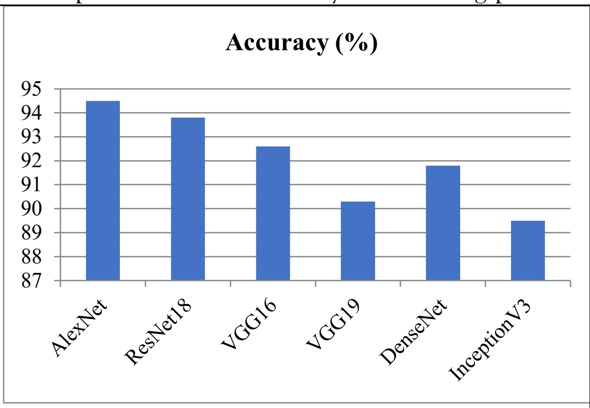

Fig 2. Comparison of Accuracy

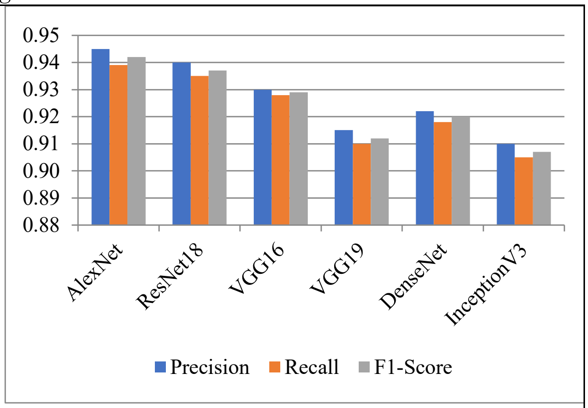

Fig 3. Comparison of performance parameters

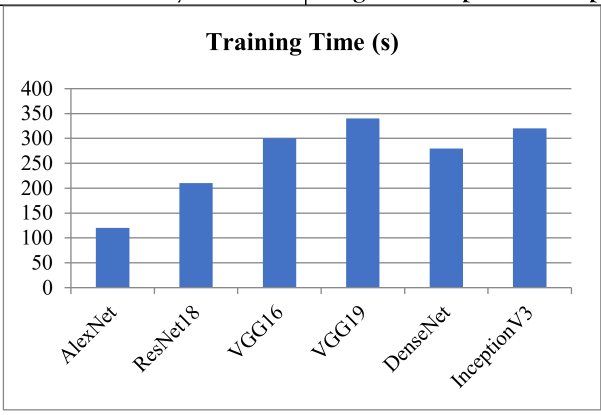

Fig 4. Comparison of Training Time

9. PRACTICAL IMPLICATIONS

Finding a model to apply should be application-specific; the results reveal that this is not always achievable and that one should find a happy medium between accuracy and computational efficiency. For broad uses where processing capability and resources might be limited, models such as AlexNet appear to be a logical answer. AlexNet excels in environments with limited resources because of its remarkable accuracy and low computational requirements. Scalable and real-time, our model may effectively identify tomato leaf diseases without depending on strong hardware. Conversely, if maximum accuracy and recall is the goal, deeper models might be better suited. Particularly helpful in settings where misclassifications might have significant consequences, like as research or medical environments, these models are excellent at gathering complicated data and generating very precise conclusions. These models use more computer resources but their remarkable accuracy helps them to be successful in situations that can support their processing needs. The findings indicate that the model to be selected should be dictated by the criteria of the application, including the amount of deployment, the degree of computing power availability, and the necessary accuracy. More solid models might be used in cases where computing constraints are not a factor and maximum accuracy is absolutely important. This methodical strategy for choosing a model guarantees that it is both efficient and well-suited to the deployment situation's constraints.

10.CONCLUSION

Work underlines how well transfer learning addresses tomato leaf disease detection. In tomato disease detection, particularly in low-resource environments, AlexNet proved to be the most accurate and efficient among six pre-trained models. AlexNet's somewhat simple architecture provides computationally efficiency, thereby allowing its implementation in settings with little resources to nevertheless achieve significant accuracy. By enabling fast disease detection made possible by accurate disease pattern categorisation of the model, farmers may thereby regulate plant health by responding early on. Even a highly performing model may have its accuracy compromised by the complexities of real-world agricultural situations, such as fluctuating illumination, disease stages, and environmental factors, as pointed out in the research. To make the model more useful in the real world, researchers want to incorporate domain-specific features and broaden the dataset to include different agricultural settings in future research. This innovation will help the model deal with field condition variance by improving its generalisability over a wide range of climates, soil types, and agricultural techniques. Incorporating real-time monitoring technologies such as drones and smartphone appscan that provide diagnoses to farmers while they are on the road and fine-tuning the model with more specific datasets are two more ways to enhance the system's usefulness. Sustainable agriculture and better crop management are the goals of this research, which seeks to solve these issues by creating more robust and flexible disease detection systems based on deep learning.

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