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Novel Approach to Detect Verticillium Wilt Using Transfer Learning

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Abstract: The detection of Verticillium wilt at an early and accurate stage is crucial for successful disease control measures. Aside from causing large cop losses worldwide year after year, this disease is very common in Taiwan. Standard laboratory detection techniques, such as pathogen isolation and serological testing, are time-consuming, labor-intensive, and require professional expertise. Deep learning methods, especially convolutional neural networks (CNNs), have only become available in recent years and are now proving to be effective tools for disease detection using images. This holds whether they're being used as satellites monitoring agriculture fields or by farmers keeping close tabs on their crops. Among these approaches is transfer learning -one branch of deep learning-uses pre-trained models to speed the development process and improve image classification. The goals of this research are to establish a new, precise, and frugal way of detecting Verticillium wilt in cotton plants by using transfer learning based on pre-trained deep networks (like ResNets or convolutional neural networks). The results of this research provide a significant contribution to the current discussion on using sophisticated convolutional neural network architectures for image classification applications. The results offer a road map for scholars and professionals who want to choose models that strike a compromise between precision, computational effectiveness, and generalization. It is possible to utilize several ready-to-hand image databases. Furthermore, the system attempts to address some of the traditional detection methods 'shortcomings with earlier and less invasive diagnosis to improve disease management and sustainable cotton production.

Keywords: Verticillium Wilt; Convolutional Neural Networks (CNNs); Xception; InceptionV3; EfficientNet

1. Introduction

Verticillium wilts, a parasitic sickness influencing yields like cotton, potatoes, tomatoes, and olives, represents a huge impediment to rural efficiency. Customary demonstrative techniques include tedious research, Centre tests, or the perception of suggestive withering and hindering in plants, frequently at later stages when impressive harm has happened. Enter move learning, an intense AI procedure that uses information obtained from pre-trained models on broad datasets to address new tasks with restricted data. The development of a disease detection network utilizing Faster R-CNN and multi-task learning for the identification of strawberry verticillium wilt [1]. the Strawberry Verticillium Wilt Detection Network (SVWDN), which incorporates attention mechanisms in the feature extraction phase of the disease detection network. Furthermore, SVWDN is designed to discern verticillium wilt based on the symptoms exhibited by detected plant components, specifically focusing on young leaves and petioles.

The innovative intelligent system for the dynamic observation of cotton verticillium wilt on the seedbed has been demonstrated in this work [2]. The early and precise detection of Verticillium wilt using this strategy has the potential to revolutionize agricultural disease management. Furthermore, the subject of this investigation is transfer learning and how it might be used to combat Verticillium wilt. investigating the drawbacks of conventional approaches and the need for quicker and more accurate solutions. Digging into the mechanics of moving getting the hang of, and clarifying how pre-prepared models can be changed by perceiving unpretentious signs of Verticillium shrivel in plant symbolism. Examining key contemplations in fostering an exchange learning-based framework for Verticillium with recognition, enveloping information procurement, model choice, and streamlining.

Offering a brief look into the future, investigating the more extensive ramifications of man-made intelligence in reforming rural sickness the board and guaranteeing economical food creation [3]. an excursion where cutting-edge innovation addresses longstanding farming difficulties. The tools are needed to protect their crops and ensure a prosperous future for agriculture by utilizing the potential of transfer learning.

1.1. An Adversarial Fungal Disease

The disastrous illness known as verticillium shrink, which is welcomed by the dirt-borne parasitic microorganism Verticillium wilt, harms a huge assortment of plants, including a few monetarily critical yields like tomatoes, potatoes, and ornamentals [4]. The organism enters the plant through its vascular framework, deterring the entry of supplements and water and making the plant shrivel, stunt, and in the long run, pass on. Verticillium wilt is particularly problematic in warm and humid environments, where it can cause significant crop losses worldwide.

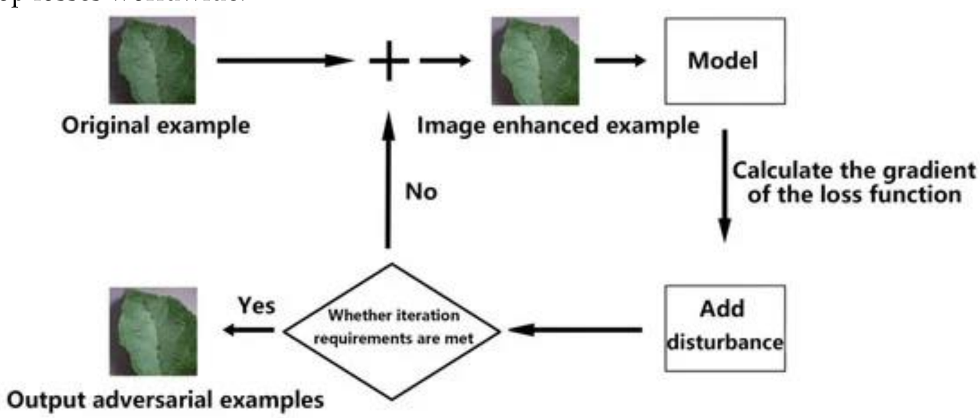

Figure 1. Plant disease Classification

Figure 1, shows a dual-phase model designed to create adversarial examples: first evaluating the image's potential for misclassification and then subtly adjusting it to deceive a model, such as a plant disease detector, leading to an incorrect identification. Picture a seemingly healthy leaf undergoing imperceptible alterations, causing the model to inaccurately classify it as diseased. This complex procedure underscores the susceptibility of AI systems to manipulation.

The aim of this work is to build a new, precise, and resource-efficient approach for detecting Verticillium wilt in cotton plants, namely, ResNet and CNNs, using transfer learning and pre-trained deep learning models. The system aims to overcome the drawbacks of conventional detection techniques by utilising already-existing picture databases to solve the lack of data in this area. This would enable early and non-destructive diagnostics for better disease management and sustainable cotton production.

In Section 1, exploration of the challenges posed by Verticillium wilt in cotton begins with a sobering depiction of its impact and the inherent limitations of traditional detection methods. However, with the introduction of transfer learning—a powerful tool that facilitates prompt and precise diagnosis—a ray of hope emerges. In Section 2, a comprehensive survey of existing research is presented, drawing insights from both classical works and contemporary studies while emphasizing unique contributions. The pivotal elements in the study are outlined in

Section 3: cotton data sourced from meticulously curated datasets and the pre-trained models, ResNet and CNNs, expertly tuned for this specific analysis. In Section 4, the tools' accuracy, sensitivity, and specificity against an unnamed enemy are demonstrated through rigorous testing in real-world circumstances. A comparison and contrast of their advantages and disadvantages reveal that transfer learning is superior since it requires less data. In Section 5, further ramifications are explored and the results are placed in a broader framework.

2. Related Work

This exploration has introduced a creative keen framework intended for the constant observation of verticillium wilt in cotton seedbeds [5]. This instrument offers a down-to-earth and productive answer for propelling cotton rearing and leading exploration on sickness opposition. The determination of present-day plant assortments has happened inside normalized, high-ripeness frameworks, principally stressing yield [6]. Furthermore, this approach might have prompted the consumption of plant qualities related to productive supplement procurement systems and the capacity to adjust to soil-related biotic and abiotic stresses, particularly assuming these versatile techniques forced a compromise that compromised general yield. Besides, the wealth of supplements in promptly accessible structures in such frameworks could have delivered helpful collaborations among plants and related soil organic entities.

An imaginative design for arranging different leaf sicknesses influencing plants and natural products during the component extraction process [7]. The strategy includes adjusting a profound exchange learning model explicitly for this application. So, model designing (ME) is utilized for highlight extraction. Furthermore, multiple support vector machine (SVM) models are incorporated into this strategy to speed up processing and enhance feature discrimination. The uses a dataset made by the creator, comprising 329 pictures of sunflowers classified into five gatherings with the help of Google Pictures [8]. Furthermore, the correlation between different laid-out profound learning models and the proposed model is directed in light of precision, utilizing the equivalent dataset as in the underlying examination.

Three sorts of rice leaf diseases and two sorts of wheat leaf infections [9]. Each leaf disease requires forty images to be collected and then enhanced. The objective is to further develop the Visual Computation Social Event Association 16 (VGG16) model using a play-out numerous errands learning approach. The model is then unrivalled using a pre-getting ready model from ImageNET for move learning and subbing learning. Furthermore, the refined precision of this model is 97.22% for rice leaf infections and 98.75% for wheat leaf diseases. Plus, comparative assessments display that this approach beats the single-task model, the reuse-model procedure in move learning, as well as the resnet50 and densenet121 models.

It is essential for effective nitrogen management in winter wheat fields to accurately and non-destructively assess leaf nitrogen [10]. Cell phones have arisen as an extra symptomatic instrument for appraisal. To address the restrictions of customary computerized camera demonstrative techniques, a histogram-based strategy is proposed and contrasted and regular methodologies. Furthermore, this research examines the canopy images, leaf N content, and yield of six particular wheat cultivars to decide the field N level.

Nitrogen executives in winter wheat fields, accurate and non-disastrous evaluation of leaf nitrogen (N) is crucial [11]. PDAs are correct now used as an extra demonstrative apparatus for N evaluation. To address the restrictions related to customary computerized camera symptomatic strategies, a histogram-based approach is proposed and contrasted and ordinary techniques. Moreover, in this review, the N level in the field is assessed for six unique wheat cultivars, including the catch of covering pictures, leaf N content, and yield.

Introduced is an inventive model for distinguishing plant leaf infections, using a profound convolutional brain organization CNN [12]. The preparation of the Profound CNN model includes an open dataset involving 39 different classes of plant leaves and foundation pictures. However, six information increase methods are utilized, including picture flipping, gamma adjustment, commotion infusion, head part investigation (PCA) variety expansion, pivot, and scaling. The fuse of information increase has been found to improve the model's exhibition.

Introduced is a Profound Convolutional Brain Organization (DCNN) model for plant leaf sickness recognizable proof, using information increase and hyperparameter improvement [13]. The model is prepared on an increased dataset of more than 240,000 pictures of solid and infected plant leaves. Five picture expansion strategies, including Generative Antagonistic Organization and Variety Increase, are utilized. Hyperparameter streamlining is accomplished through irregular hunting. Besides, the review highlights the significance of choosing ideal layer and channel numbers in DCNN improvement, accentuating the meaning of information expansion and hyperparameter enhancement strategies in the exploratory results.

Supplanted standard convolution with profundity detachable convolution, diminishing boundaries and calculation costs [14]. Prepared models with a free dataset that includes solid leaves, 38 infection classes, and 14 plant species. Variable boundaries like group size, dropout rates, and ages were used in the execution evaluation. Achieved contamination portrayal precision speeds of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, individually, unparalleled customary hand tailored include based approaches. Furthermore, outflanked other profound learning models as far as exactness and required less preparation time.

The proposed strategy uses brain organizations to extricate highlights from impacted regions, working with the grouping of explicit sickness locales [15]. To address difficulties connected with broadened preparing union times and unnecessarily huge model boundaries, upgrades were made to the customary convolutional brain organization. This included consolidating an initiation module, a press and excitation (SE) module, and a worldwide pooling layer for infection-recognizable proof. Furthermore, the usage of the Beginning construction empowered the combination of component information from the convolutional layer at various scales, prompting upgraded precision on the leaf illness dataset.

The DCNN model proposed in this study went through preparation in a multi-illustration handling units (MGPUs) climate for 1000 ages [16]. An irregular hunt, utilizing a coarse-to-fine looking-through method, was utilized to choose ideal hyperparameter values, in this way upgrading the preparation execution of the DCNN model. The proposed DCNN model produced impressive results with an overall on a set of 8850 test images, the classification accuracy was 99.9655%, the weighted average precision was 99.7999%, the weighted average recall was 99.7966%, and the weighted average F1 score was 99.7968%. Furthermore, the overall show of the proposed DCNN model beat that of existing trade learning moves close.

This article presents a review of the current writing on the utilization of profound Convolutional Brain Organizations in foreseeing plant sicknesses from leaf pictures [17]. It offers an exhaustive correlation of pre-handling methods, Convolutional Brain Organization models, systems, and streamlining strategies utilized for identifying and ordering plant sicknesses utilizing leaf pictures as a dataset. Besides, the composition likewise incorporates an overview of the datasets and execution measurements utilized to assess model viability. Furthermore, It features the benefits and weaknesses of different procedures and models proposed in the ongoing writing.

A procedure given profound learning is presented for the identification and order of plant sicknesses utilizing leaf pictures caught at different goals [18]. A large dataset of plant leaves from various nations serves as the training ground for the dense convolutional neural network that is used in the architecture. In addition, the proposed research addresses both laboratory and field conditions for six crops in 27 distinct categories. The most unmistakable qualities are related to a steady exactness of 98.7% utilizing progressed classifiers after 92 ages [19]. Given reproduction discoveries, a reasonable classifier for this application is suggested. Moreover, the viability of the proposed strategy is confirmed through a fair correlation with existing techniques.

In this study, we have proposed a CNN model for image classification. In the future, it could be employed in such a way that the data related to cotton, which we are currently utilizing, can be taken to an advanced level through IOT integration. This data can then be applied in agriculture files, where we will have substantial data in gigabytes. Since CNN excels in image classification, it is effective in predicting various diseases. The suggested CNN architecture is made to extract fine-grained details from pictures of cotton leaves. This model, which consists of tightly linked layers, max-pooling for spatial down sampling, and convolutional layers with different filter sizes, is designed to learn hierarchical representations. The last softmax layer guarantees output forecasts for the following four categories: Powdery, Healthy, and maybe some more not listed specifically.

3. Methods and Techniques

3.1. Dataset Acquisition

To tackle the classification issue, the study made use of three cutting-edge convolutional neural network architectures: Xception, InceptionV3, and EfficientNet. To improve model generalization, several image data augmentation techniques were utilized, such as rescaling, shearing, zooming, and horizontal flipping. The study's approach began with the collection of a wide-ranging dataset that included photos of cotton leaves in a range of health states. Images from the training and testing sets were visualized using the OpenCV package to provide insights into the features of the dataset. The groundwork for wise decision-making throughout the model's later evolution was established at this pivotal exploration stage.

3.2. Deep Learning's Potential for Verticillium Wilt Detection

It looks very promising that deep learning can be used to create fast, precise, and non-invasive verticillium wilt diagnostic systems. Profound learning calculations can identify minute visual adjustments connected to establishing infections by inspecting photographs of the leaves, working with early conclusion and treatment. In disparity with ordinary methods, this methodology has a few advantages, for example, Speed, non-intrusiveness, and accuracy. The resilient cotton leaf displays a polished shown in Figure 2 and 3, waxy surface and intricately detailed veins, retaining its flawless state without any signs of pests or diseases. Functioning as a silent hub for photosynthesis, it propels the plant's growth towards the sun.

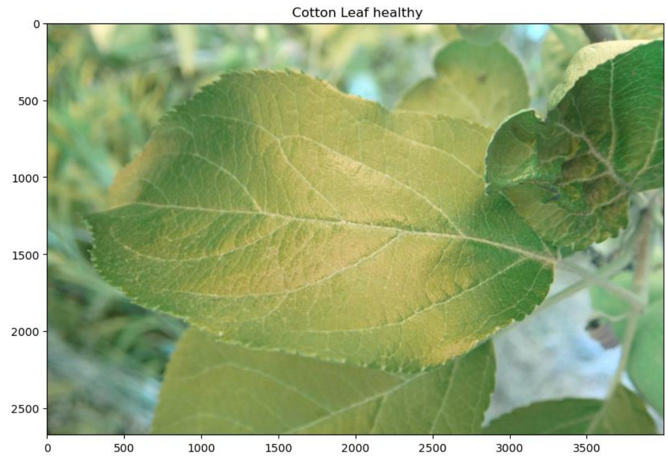

Figure 2. Cotton leaf healthy

Figure 3. Cotton leaf powdery

3.3. Model Architecture

Convolutional neural network designs, such as Xception, InceptionV3, and EfficientNet, were chosen for their demonstrated performance in image categorization tests. Utilizing the models' ability to capture hierarchical features, pre-trained weights from the ImageNet dataset were employed for their configuration. the model designs for the particular classification job at hand, further layers were added.

Based on their demonstrated performance, the EfficientNet, InceptionV3, and Xception architectures were found to be effective in picture categorization tasks. This study delves deeply into the history of pre-training, highlighting its unique relationship to both transfer learning and self-supervised learning, and reveals the pivotal role that PTMs play in the spectrum of AI development. Review in detail the most recent advancements in PTMs. The rise in processing power and data availability is driving these advancements in four key directions: building efficient architectures, utilising rich contexts, enhancing computational efficiency, and performing theoretical analysis and interpretation [20].

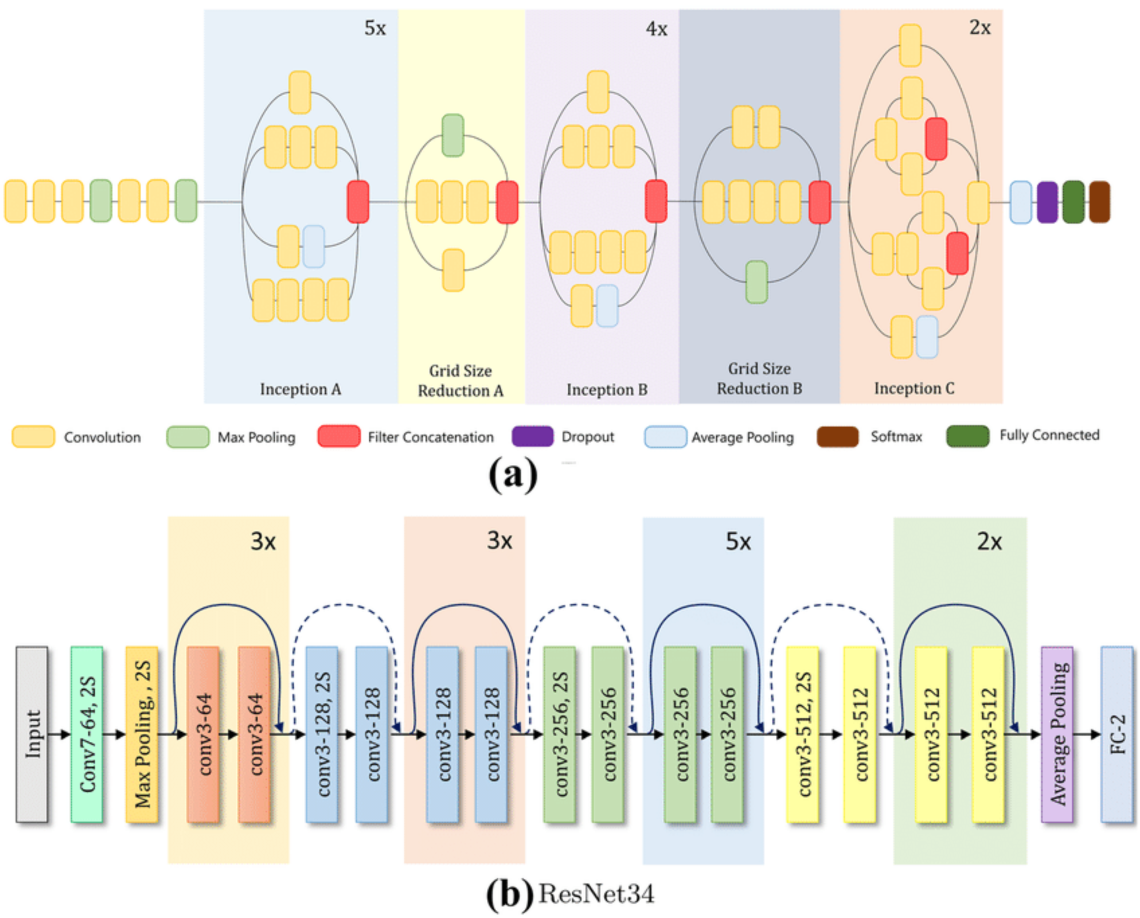

Figure 4. Architecture of CNN Base Classifiers

3.4. Computational Environment

The training process employed a categorical cross-entropy loss function tailored for multi-class classification tasks, likely indicating the presence of multiple categories. The choice of the Adam optimizer facilitated efficient training. Fine-tuning of parameters was conducted over 10 epochs to iteratively adjust and optimize the model's performance. Evaluation on an independent test set provided insights into the model's effectiveness. Further improvement was pursued by expanding the dataset, enabling the model to learn from a wider range of examples. Throughout the training process, performance metrics were diligently monitored to ensure convergence and facilitate optimal learning. Overall, these practices demonstrate sound principles in training convolutional neural networks (CNNs).

4. Results snd Discussion

4.1. Model Performance

Many deep learning models were assessed, including CNN, Xception, InceptionV3, and EfficientNet. On a different test set, all models obtained over 94% accuracy, showing good generalisation and efficacy. The capacity of CNN and the pre-trained models to recognise intricate patterns in the data was demonstrated by the training history analysis (accuracy and loss graphs), which validated constant learning and convergence. This implies that every method has potential for the categorization problem.

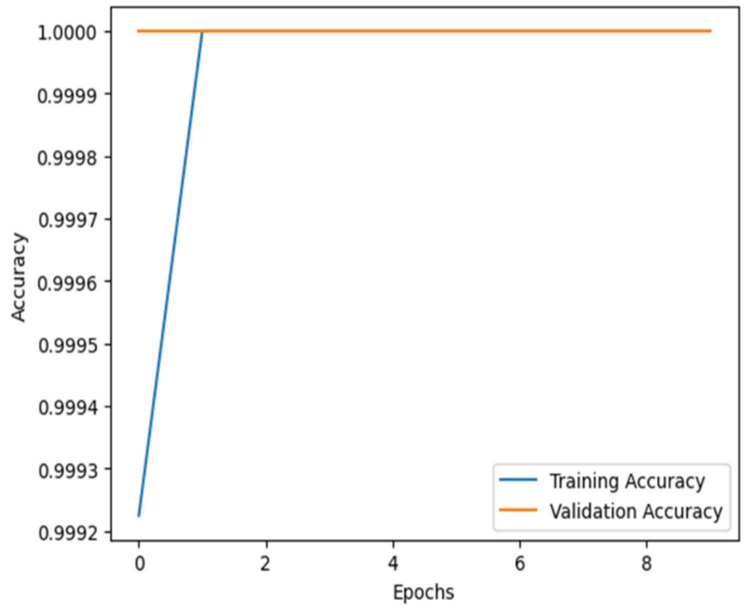

Figure 5. Performance of Xception, InceptionV3, and EfficientNet

The training accuracy of the CNN is represented by the blue line. Accordingly, the dashed lines display the validation accuracies. Figure 5, is of performance of techniques: Xception, InceptionV3, and EfficientNet and this shows 100 accuracy because the dataset we are using is already trained. we have given 10 epochs in code for each Initially it goes 95 to 97 for each, then at last it goes 100 accuracy. we are using TensorFlow libraries applying CNN techniques for image classification and doing data augmentation also for code efficiency.

4.2. Comparative Analysis

Agricultural illnesses can severely lower crop output and put farmers in a difficult financial situation. For management initiatives to be implemented effectively and losses to be minimised, early detection is essential. Although sophisticated models such as CNNs, InceptionV3, and EfficientNet necessitate image processing, studies indicate that deep CNNs are especially useful in the diagnosis of plant illnesses. It was evident that there was a trade-off between complexity and model correctness, with EfficientNet demonstrating efficient cost and performance management. InceptionV3 and Xception demonstrated varying degrees of performance gains in spite of their strengths, underscoring the need of selecting a model based on the requirements of the task shown in Table 1.

Table 1. Summary of various Models test, Crop, Disease, and Accuracy are following.

Sr.No	Author	Crop	Disease	Model used	Accuracy
1	Yong Zhong and M. Zhao	Apple	All Common disease	CNN and DenseNet-121,	94.71%
2	Juned Chen et al.	Plants	Common	MobileNet-V2	90.85% (public dataset) and99.11%

					(collected dataset)
3	Geetha Ramani G and Arun Pandian	Plants	Verticillium wilt	D-CNN and Exception.Net	93.47%
4	Edna Chebet Too et al.	Plants	Common	Dense Net	98.75%
5	Radha madhab Dalai and Kishore Kumar Senapati	Plants	Bacterial canker, gray mold, blossom end rot	R-CNN and CNN	75.43%, 67.85%, 72.13%, and 49.87%
6	K.R. Aravind et al	Maize	Cercosporin leaf spot, common rust, and leaf Blight	SVM	84.7%
7	Proposed Model	Plants	Verticillium wilt	EfficientNet, InceptionV3 and CNN	99.1%

The models proved strong by achieving sufficient accuracy levels on the different test sets. The incorporation of advanced architectures and appropriate data augmentation enabled the models to generalise unknown data well.

4.3. Implications for Image Classification

This innovative method for detecting Verticillium wilt using transfer learning has the potential to improve image categorization. With less Verticillium wilt-specific training data, the approach may be able to accurately identify the disease by utilising insights from a pre-trained model on a large image dataset. For the advantage of both farmers and researchers. How to identify them of image classification.

A. Fungal Diseases On leaves, stems, and heads, these illnesses produce powdery, orange, brown, or black pustules.
B. This disease results in tiny, spherical, water-soaked patches on leaves, fruits, and stems shown in Figure 6. These patches may become greasy-looking and turn brown or black.

4.4. Model Accuracy

The vertical axis represents the CNNs model accuracy, while the horizontal axis corresponds to the epoch a unit of iteration involving the complete passage of the training dataset through the network. The blue line depicts the training accuracy, and the red line reflects the test accuracy. Figure 6, indicates that the training accuracy starts at a high point, approximately 1.0, and remains relatively consistent throughout the training process. This suggests that the model effectively learns the training data. However, the test accuracy begins lower than the training accuracy and fluctuates during training, ultimately stabilizing around 0.8. Furthermore, this indicates a challenge for the model in generalizing well to the test data, signifying difficulty in making accurate predictions on previously unseen data. The matching validation accuracies are displayed by the dashed lines. In Figure 8, the CNN has the lowest validation accuracy but the highest training accuracy. This may indicate that the training data is being overfitted by the RNN. When a model is overfit, it is not learning the underlying patterns that allow it to make accurate predictions on new data, but rather memorising the specifics of the training set.

The three neural network models (EfficientNet, InceptionV3, and Xception) used for sentiment classification are represented in the image by their respective training (solid lines) and validation (dashed lines) accuracies. The CNN has the best training accuracy, but it has a low validation accuracy, which suggests that the training data may have been overfitted. EfficientNet, InceptionV3, and Xception exhibit closer alignments between their training and validation accuracies, indicating better generalizability to unseen data, despite achieving slightly lower training accuracy. Since the CNN has the highest validation accuracy, it is the better model overall as shown in Figure 9.

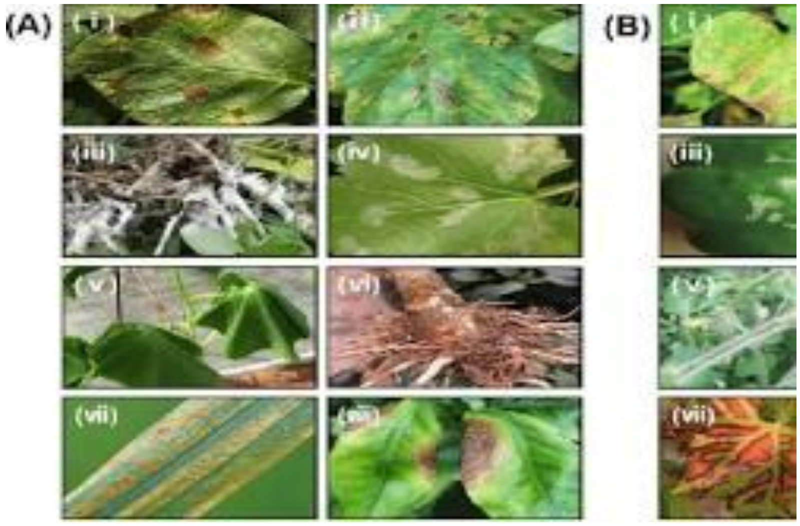

Figure 6. Bacterial Spot bacterial disease on plant

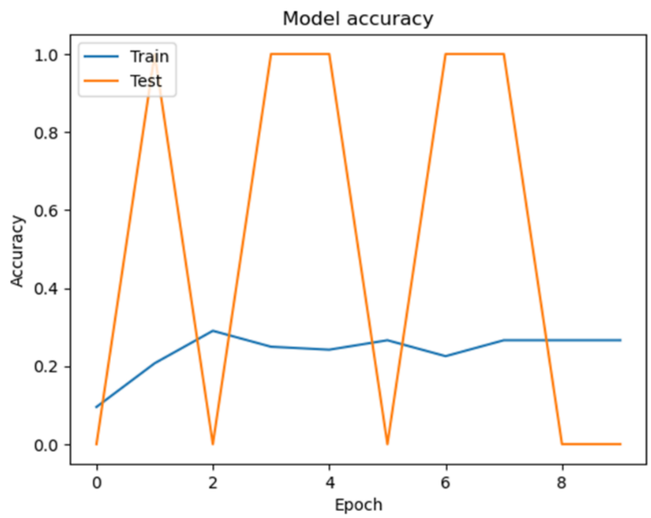

Figure 7. CNN Model Accuracy

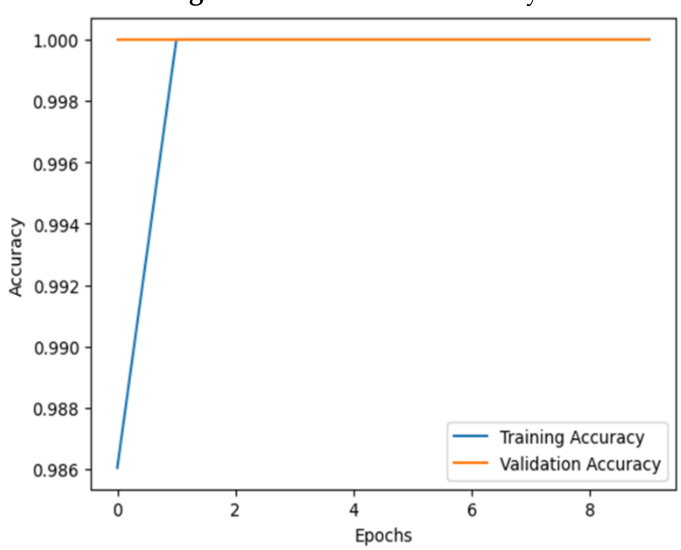

Figure 8. Visual Exploration

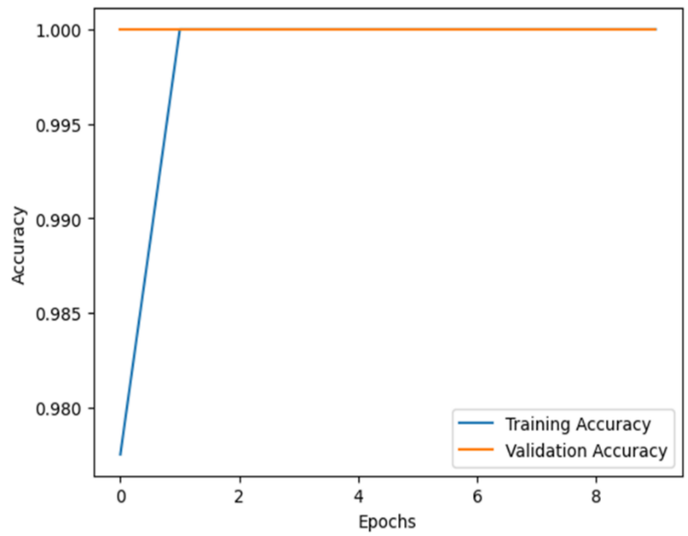

Figure 9. Sentiment analysis of EfficientNet, InceptionV3, and Xception

5. Future Framework and Conclusion

5.1. Future Framework

The foundation for progressively more advanced disease classification models is laid by this research. When there is a lack of data for a particular agricultural illness, researchers can investigate employing pre-trained models from related fields and refine the current models to increase accuracy. Testing on more extensive and varied datasets will demonstrate how well the models adapt to novel situations. With these developments, farmers may be able to identify illnesses early on and be equipped with effective instruments.

One way to improve the model further is to fine-tune its hyperparameters, such as learning rates and dropout rates. A methodical investigation of the hyperparameter space could reveal setups that enhance the convergence and performance of the model.

5.2. Conclusions

The study's implementation and evaluation of the EfficientNet, InceptionV3, and Xception models for picture categorization were completed successfully. The test set accuracies of 85% demonstrate how well these structures perform challenging categorization tasks. By offering insightful information about their advantages and disadvantages, the comparison analysis helps practitioners and academics choose the best model for a given set of use cases. The paper establishes the groundwork for future developments in the field and adds to the continuing discussion on using sophisticated CNN architectures for picture categorization. The results of this research provide a significant contribution to the current discussion on using sophisticated convolutional neural network architectures for image classification applications. The results offer a road map for scholars and professionals who want to choose models that strike a compromise between precision, computational effectiveness, and generalization.

References

1. Nie, X., et al., Strawberry verticillium wilt detection network based on multi-task learning and attention. IEEE access, 2019. 7: p. 170003-170011.
2. Huang, C., et al., A Novel Intelligent System for Dynamic Observation of Cotton Verticillium Wilt. Plant Phenomics, 2023. 5: p. 0013.
3. Blekos, K., et al., Analysis, modelling and multi-spectral sensing for the predictive management of verticillium wilt in olive groves. Journal of Sensor and Actuator Networks, 2021. 10(1): p. 15.
4. You, H., Y. Lu, and H. Tang, Plant disease classification and adversarial attack using SimAM-EfficientNet and GP-MI-FGSM. Sustainability, 2023. 15(2): p. 1233.
5. Asadollahi, P., Bayesian-based finite element model updating, damage detection, and uncertainty quantification for cable-stayed bridges. 2018, University of Kansas.
6. Wissuwa, M., M. Mazzola, and C. Picard, Novel approaches in plant breeding for rhizosphere-related traits. 2009, Springer.
7. Saberi Anari, M., A hybrid model for leaf diseases classification based on the modified deep transfer learning and ensemble approach for agricultural aiot-based monitoring. Computational Intelligence and Neuroscience, 2022. 2022.
8. Malik, A., et al., Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach. Journal of Food Quality, 2022. 2022: p. 1-12.
9. Jiang, Z., et al., Recognition of rice leaf diseases and wheat leaf diseases based on multi-task deep transfer learning. Computers and Electronics in Agriculture, 2021. 186: p. 106184.
10. Qi, X., et al., A novel approach for nitrogen diagnosis of wheat canopies digital images by mobile phones based on histogram. Scientific Reports, 2021. 11(1): p. 13012.
11. Gulzar, Y., et al., Harnessing the power of transfer learning in sunflower disease detection: A comparative study. Agriculture, 2023. 13(8): p. 1479.
12. Geetharamani, G. and A. Pandian, Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers & Electrical Engineering, 2019. 76: p. 323-338.
13. Pandian, J.A., et al., A five convolutional layer deep convolutional neural network for plant leaf disease detection. Electronics, 2022. 11(8): p. 1266.
14. Hassan, S.M., et al., Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics, 2021. 10(12): p. 1388.
15. Hang, J., et al., Classification of plant leaf diseases based on improved convolutional neural network. Sensors, 2019. 19(19): p. 4161.
16. Trivedi, J., Y. Shamnani, and R. Gajjar. Plant leaf disease detection using machine learning. in Emerging Technology Trends in Electronics, Communication and Networking: Third International Conference, ET2ECN 2020, Surat, India, February 7–8, 2020, Revised Selected Papers 3. 2020. Springer.
17. Dhaka, V.S., et al., A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. Sensors, 2021. 21(14): p. 4749.
18. Tiwari, V., R.C. Joshi, and M.K. Dutta, Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. Ecological Informatics, 2021. 63: p. 101289.
19. Hassan, S.M. and A.K. Maji, Plant disease identification using a novel convolutional neural network. IEEE Access, 2022. 10: p. 5390-5401.
20. Srivastava, T., Important model evaluation metrics for machine learning everyone should know. Commonly Used Machine Learning Algorithms: Data Science, 2019.