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A Transfer Learning-based Approach for the Classification of Tomato Leaf Diseases using Modified Classification Base

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ABSTRACT
Diseases affecting tomato leaves represent a significant risk to agricultural yield and quality, making swift and accurate identification essential for sustainable farming and reducing reliance on herbicides. Traditional manual evaluation methods are labor-intensive, subject to bias, and more likely to be erroneous. Deep learning, particularly via transfer learning (TL), has revolutionized plant disease detection by providing automated and highly precise classification. This study introduces a TL based customized classification model that classifies tomato leaf diseases into four unique categories namely Early Blight, Late Blight, Yellow Curl Leaf Disease, and Healthy leaves. The model is developed utilizing a diverse collection of accurately labelled images of both healthy and diseased tomato leaves sourced from the Plant Village dataset, a renowned and high-caliber dataset available on Kaggle. To improve performance, data augmentation techniques (such as rotation, flipping, brightness, and contrast modifications) are utilized, enhancing robustness and reducing overfitting. The effectiveness of the model is evaluated using metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis, illustrating its superior classification performance compared to conventional machine learning methods. The results shows that the customization done in the classification part of the popular deep learning-based architectures namely VGG16, VGG19, ResNet50, InceptionV3, AlexNet and DenseNet, for the classification of diseases achieves comparable accuracy.

General Terms
Transfer learning, Deep Learning

Keywords
Classification, Deep learning model, transfer learning, tomato leaf disease, plant village dataset

1. INTRODUCTION
One of the most popular fruits that people eat every day is the tomato. The global consumption rate of tomatoes is high since they are used in condiments like sauce, ketchup, and puree. The annual consumption of tomatoes in Europe, per-person, is quite large. Every year, each individual eats roughly 42 kg of tomatoes and more [1].

Around the world, tomatoes are one of the most frequently cultivated and economically important crops. Over 180 million tons of tomatoes are produced worldwide each year, according to the Food and Agriculture Organization (FAO). As a result, tomatoes are essential to both home and economies of many nations specifically in areas where agriculture contributes significantly to employment and GDP.

It's essential to identify tomato leaf diseases early and accurately. It helps farmers act quickly to stop the spread of illness. Higher yields and higher-quality crops are guaranteed.

It is difficult to understate the significance of early disease detection in agriculture. To stop the development of disease and reduce productivity losses, farmers can use smart crop rotations or accurate pesticide applications thanks to early detection. Additionally, by maintaining maximum crop yield, prompt disease identification is essential to minimizing financial losses and maintaining food security. The main goals of the paper [2] are to use transformer encoder blocks to accurately identify tomato leaf illnesses and to capture complex geographic relationships in leaf images.

Fruit color, texture, and flavor are all changed as a result of the complex procedure of tomato ripening, which involves physiological and biochemical changes. The production and respiration of ethylene increases during ripening, just like in other citrus fruits [3]. The function of ripening genes, like those of many tomato genes, were typically found by forward genetics through the selection of individuals showing a ripening phenotype and the subsequent mapping of the genes causing these mutations by chance.

On the other side, Deep learning, inspired by the human brain, is making waves in various fields, including computer vision, medical imaging, and agriculture. Recently, the use of Convolutional Neural Networks (CNNs) has surged, proving highly effective in diagnosing plant diseases.

Fortunately, transfer learning can enhance the performance of neural networks with deep learning by avoiding complex data analysis and data-labelling efforts [4] [5].TL based methods are widely adopted and implemented in other medical domains also as mentioned in paper [6][7]. By using the classical deep learning architectures namely VGG16 [8], VGG19 [9], ResNet50 [10], InceptionV3 [11], AlexNet [12] and DenseNet [13] with modified classification base, this study aims to investigate the performances of these models in identifying plant leaf diseases.

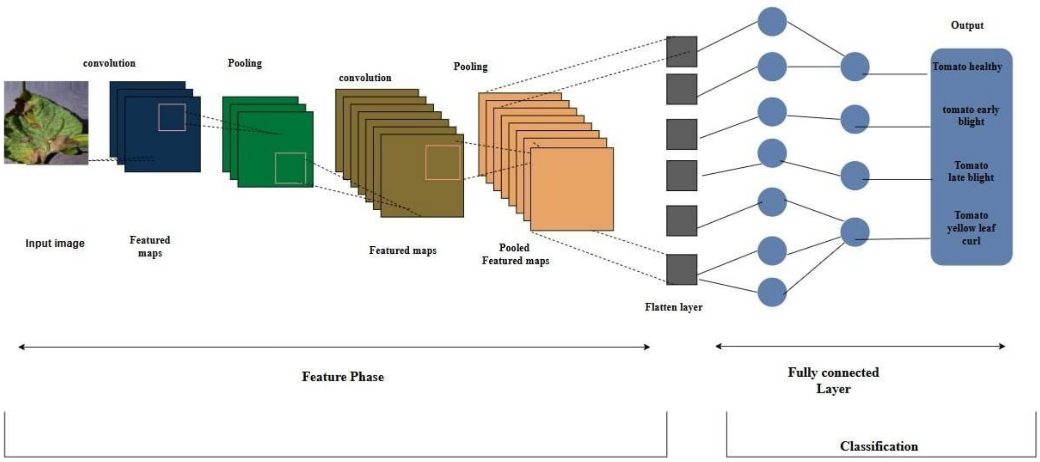

Fig 1: CNN based approach for classification of tomato leaf disease

2. LITERATURE REVIEW

This paper tries to summarize the work done in the intended field in last 4-5 years. The review is focused on the type of types of plant species used, source of data collection, year of publication, name of algo. used, pre-processing techniques used, evaluation parameters and brief findings. The detailed literature study is shown in Table 1.

3. METHODOLOGY

To accomplish the objective of identifying plant leaf diseases, the diseases are grouped into four distinct classes.

To accomplish the objective of identifying plant leaf diseases, the diseases are grouped into four distinct classes. The steps consist of collecting leaf images, preprocessing, and applying algorithms to classify the diseased leaves into one of the four predefined classes. The implemented method makes use of pre- processing of images, feature extraction, classification and performance evaluation.

3.1 Dataset used

The dataset [13] from Kaggle is used for the study purpose which is composed of

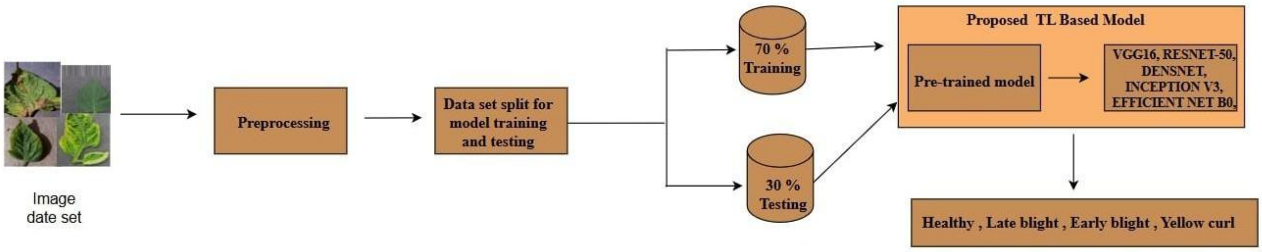

Fig 2: Methodology adopted

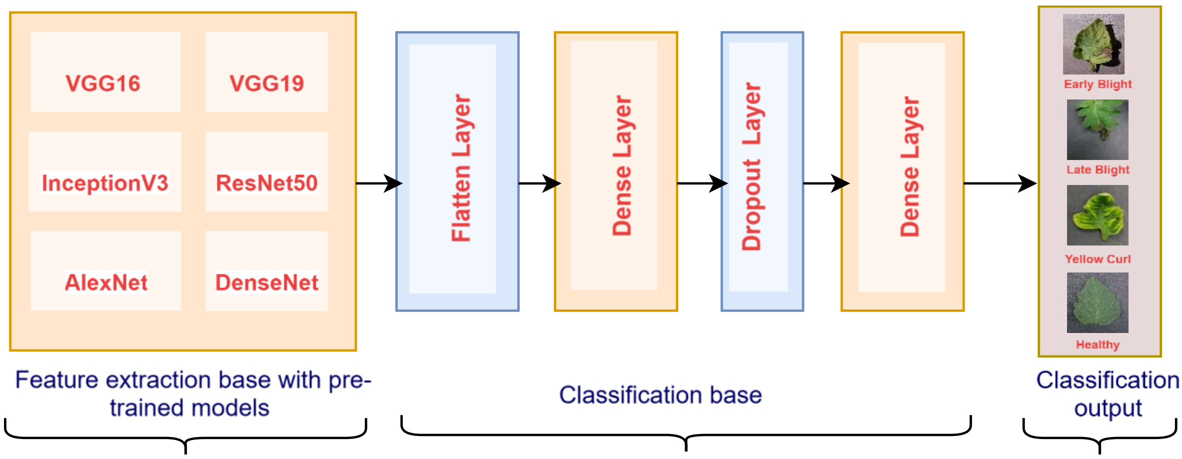

Fig 3: Modified classification base for disease classification

information associated with exceptional diseases of various plants leaves along with the tomato leaves, inclusive of tomato early blight, tomato past due blight, tomato yellow leaf curl virus, tomato healthy and others. This study only focused on only the mentioned four classes for the work. The data examined is having 9857 images; each is having size 224×224 pixels, representing numerous varieties of tomato leaf diseases.

3.2 Pre-processing

A list of parameters which are used in making data ready for training and testing purposes can be exhaustive. This paper have used width_shift_range and height_shift_range having value 0.2, horizontal_flip & vertical_flip is kept true, rotation_range is set at 30.In the first dense layer of classification base the number of neuron unit are chosen to 32 with activation function ReLu.The dropout is kept at value 0.5.In the second dense layer number of neuron unit are chosen to 4 with activation function Softmax.The learning rate is set at 0.001.

3.3 Data split for training and testing

Typically, a dataset is divided into two or more subsets: a training set and a testing set, and sometimes a validation set. In the training set, 70% of the data, is used to train the deep model and for testing the proportion is set to 30%. It's vital that the data split is random and representative to avoid introducing biases and to ensure both sets reflect the overall data distribution.

3.4 Proposed TL based method

Deep learning, particularly via transfer learning (TL), has revolutionized plant disease detection by providing automated and highly precise classification. This study introduces a TL based customized classification model that classifies tomato leaf diseases into four unique categories namely Early Blight, Late Blight, Yellow Curl Leaf Disease, and Healthy leaves. This paper explores the performance of popular pre-trained models with adopted classification base. The pre-trained models which are experimented with new classification base are VGG16, VGG19, ResNet50, InceptionV3, AlexNet and DenseNet.

3.5 Evaluation of result

The performances of the models are evaluated with the help of accuracy and loss function. Also, the other crucial and important parameters considered are given below. The comparison chart is shown in the end.

$$\text{Accuracy(A)} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

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

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

$$\text{F1 Score} = \frac{2 * \text{P} * \text{R}}{\text{P} + \text{R}}$$

4. EXPERIMENT SETUP

Google Colab provides an accessible and powerful experiment setup for deep learning, leveraging cloud-based Jupyter notebooks with free access to GPUs and TPUs. The experiments were conducted on the free GPU tier of this Google Colab. (Tesla T4, 16 GB VRAM).

5. RESULTS AND DISCUSSION

Comparing the results from the accuracy and loss curves, given below, for VGG16, ResNet50, InceptionV3, AlexNet, VGG19, and DenseNet models the following conclusion can be observed:

Best Generalization/Performance: DenseNet appears to be the most robust, showing consistently high accuracy and low loss with minimal overfitting. VGG16, VGG19, and InceptionV3 also demonstrate strong validation performance.

Training Stability: DenseNet exhibits the most stable training. ResNet50 shows the most instability, with significant fluctuations in both accuracy and loss. AlexNet also shows notable oscillations.

Overfitting Tendencies: AlexNet shows a clearer gap between training and validation performance, indicating more overfitting. ResNet50's erratic behavior makes it hard to definitively classify as just overfitting, but it's not generalizing well. VGG16, VGG19, InceptionV3, and DenseNet generally generalize well, although InceptionV3 and VGG19 have some spikes in training metrics that could suggest minor overfitting at those points.

In conclusion DenseNet appears to be the most effective model, followed closely by VGG16, VGG19, and InceptionV3. ResNet50 and AlexNet demonstrate more challenging training dynamics and less optimal generalization. However, these interpretations are drawn on limited training of the model. In the realistic sense the training must be exhaustive. On the basic level of training these results are significant and can be accepted. In future, the results van be evaluated on more realistic ground and with more models and epochs. Also, the models proposed is very specific to type of crop and related subset of disease classes. In future a more generous model can be developed which will be able to classify more diseases related to variety of crop leaves.

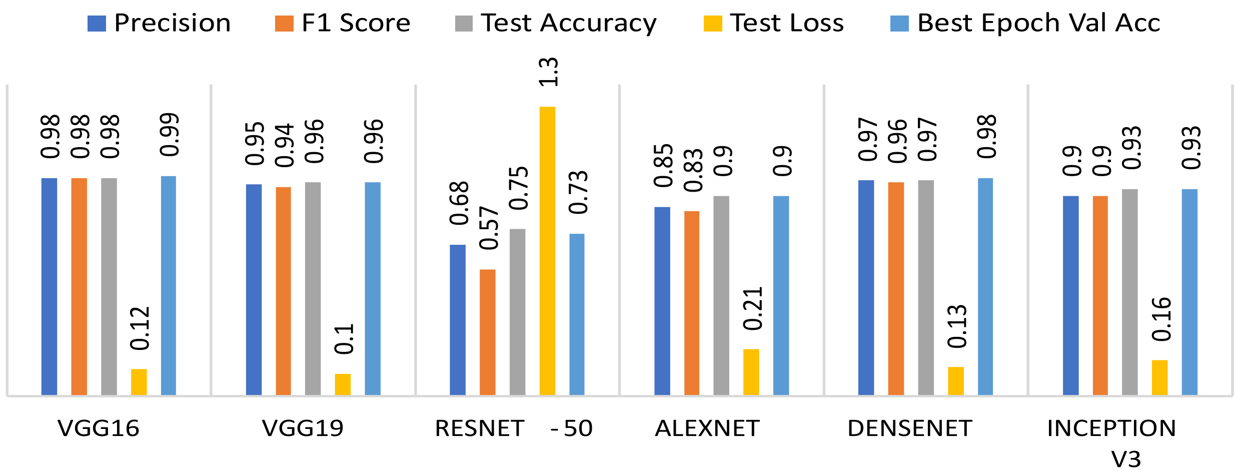

Fig 4: Comparison of all model performances

Table 1: Literature review

Paper	Types of Plant Species Used	Source of Data Collection	Publication Year	Name of Algo. Used	Pre-processing Techniques Used	Evaluation Parameters	Findings/Results
[14].	Apple, Potato, Tomato, Pepper	Plant Village Dataset	2024	CNN based model	Image Augmentation, Normalization	Accuracy, Precision, Recall, F1-Score	CNN achieved high accuracy in disease classification for different crops.
[15].	Tomato, Corn, Wheat	Kaggle (Open Access)	2024	ResNet-50, VGG16	Image Augmentation, Scaling	Accuracy, Sensitivity, Specificity	ResNet-50 outperformed VGG16 in detecting crop diseases with high accuracy.
[16].	Rice, Cotton, Maize, Wheat	NM-AIST and the Tanzania Agricultural Research Institute (TARI)	2024	CNN based model	Grayscale Conversion, Noise Removal	F1-Score, Accuracy, Precision	SVM performed well in distinguishing crop diseases with high precision.
[17].	Paper, Tomato, Potato	Real-time camera or mobile	2023	ResNet50	Data Augmentation, Normalization	F1-Score, AUC, ROC Curve	CNN achieved superior results for plant disease prediction, with high recall.
[18].	Rice	Kaggle	2024	CNN based model	Image Augmentation, Rescaling	Precision, Recall, F1-Score	Model achieved high accuracy with reduced misdetection.
[19].	apple	Plant Village Apple leaf Dataset	2024	Deep Learning based model	Noise Reduction, Color Normalization	Accuracy, Precision, Recall	Deep learning models showed high accuracy and robustness for disease Classification.
[20].	Soybean, Maize, Rice, Wheat	Github	2024	Deep Learning based model	Normalization, Data Augmentation	Accuracy, AUC, F1-Score	DNNs performed robustly in predicting and Detecting leaf diseases.
[21].	Maize, Soybean, Rice, Wheat	crop leaf Image Data	2024	Deep Learning based model	Image Augmentation, Feature Scaling	F1-Score, Accuracy, Precision	CNN showed better results in terms of classification compared to SVM.
[22].	Rice	Fujian Institute of Subtropical Botany, Xiamen, China	2020	VGGNet, CNN	Grayscale Conversion, Data Augmentation	Precision, Recall, F1-Score	InceptionV3 outperformed CNN in identifying tomato diseases.
[23].	Tomato	Roboflow	2024	Deep Learning based model	Data Augmentation, Normalization	Accuracy, Precision	Deep Neural Networks showed high accuracy and reduced false positives.
[24].	Corn, Rice, Rape	AgriPest Dataset	2024	CNN based model	Normalization, Feature Selection	Accuracy, Precision, Recall	CNN gave excellent Detection results for tomato, rice, and potato.
[25].	Tomato	Kaggle	2024	CNN based model	Grayscale Conversion, Rescaling	Accuracy, F1-Score, Sensitivity	CNN achieved the best results for crop disease detection.
[26].	Tomato	Kaggle	2024	CNN based model	Data Augmentation, Image Scaling	Accuracy, F1-Score, Precision	CNN model performed well with minimal training time for rice diseases.
[27].	Vegetables, Fruit	Github	2024	Deep Learning based model	Data Augmentation, Image Scaling	Accuracy, F1-Score, Precision	DNN showed better detection rates for fungi diseases.
[28].	Paddy crop	Kaggle	2024	Convolutional Neural Network (CNN)	Grayscale Conversion, Noise Reduction	Precision, Recall, Accuracy	SVM model performed well in detecting maize diseases with good precision.

[29].	Paper, Tomato, Potato	Plant Village Dataset	2024	K-Nearest Neighbour (KNN)	Feature Scaling, Augmentation	Accuracy, F1-Score, Sensitivity	KNN showed high accuracy in detecting multiple potato diseases.
[30].	Soybean, Rice, Wheat	BSDS500	2024	CNN based model	Image Normalization, Feature Extraction	Accuracy, F1-Score, Precision	Evaluated performance of each method or combination against expert identified contours.
[31].	Tomato	Plant Village Dataset	2024	Vision Transformer, Inception V3	Data Augmentation	Accuracy, Precision, Recall	A ViT-based models achieved 90.99% accuracy in identifying 10 tomato leaf diseases.
[32].	Tomato	Kaggle	2024	CapsNet, CNN	Data Augmentation, Normalization	Accuracy, F1-Score, Sensitivity	96.39% accuracy in detecting 10 tomato leaf diseases, outperforming CNNs by effectively capturing spatial features like spot shape, color, and location.
[33].	Tomato	Plant Village Dataset	2023	CapsNet,, SVM,	Data Augmentation, Normalization	Accuracy, F1-Score,	The CapsNet-SVM model achieved 93.41% accuracy in classifying tomato leaf diseases, outperforming existing methods through effective feature extraction and robust classification.
[34].	Tomato	Plant Village Dataset	2024	CapsNet, ResNet	Noise Reduction, Feature Extraction	Precision, Recall, Accuracy	The SE-SK-CapResNet model achieved up to 98.58% accuracy by combining CapsNet and enhanced ResNet for robust plant leaf disease classification.
[35].	potato, grape, apple, corn	Plant Village Dataset	2023	ACO CNN, SGD	picture acquisition, image separation	F1-Score, Accuracy, Precision	The ACO-CNN model achieved high accuracy in classifying plant leaf diseases.
[36].	corn	laboratory in Hyderabad	2024	MobileNetV2 model	Data Augmentation, Normalization	Precision, Recall, Sensitivity	MobileNetV2 showed good generalization capability in corn disease detection.
[37].	Black-papper, blueberry, corn, etc.	PlantDoc Dataset	2024	ViT and ResNet50	Image-Resizing, Noise Reduction	Accuracy, Precision, Recall	The PMF+FA method using Vision Transformers achieved 90.12% accuracy.
[38].	Maize	Plant Village Dataset	2023	CNN-RB	Image Augmentation, Feature Scaling	Accuracy, F1-Score, Sensitivity	It Detect seed diseases for quality evaluation and disease control
[39].	Wheat, Rice, Maize	Kaggle	2024	HTP data + AI/ML	Data Augmentation, Image Resizing	Accuracy, Precision, Recall	Integration of high-throughput phenotyping and AI enables precise, efficient crop trait analysis, accelerating crop improvement with reduced time and cost.
[40].	Tomato, Potato, Corn	PlantVillage Dataset	2020	FSL, InceptionV3	Feature Extraction	F1-Score, Sensitivity, Precision	Outperforming traditional transfer learning methods on small datasets.
[41].	Black-papper, blueberry, corn, etc	Kaggle	2024	CNN, KNN	Image Scaling, Feature Extraction	Precision, F1-Score, Accuracy	CNN showed superior classification ability for diseases.
[42].	Soybean, Tomato, Potato	Plant Village Dataset	2024	CNN based model	Noise Reduction, Feature Extraction	Precision, Recall, Accuracy	CNN provided strong identification results for soybean diseases.

[43].	Sugarcane	Plant Village	2018	CNN based model	Data Augmentation, Image Pre-processing	Precision, Recall, F1-Score	The study highlights CNNs as a powerful deep learning approach for agricultural image analysis, with a case application in sugarcane and broader relevance across crop monitoring tasks.

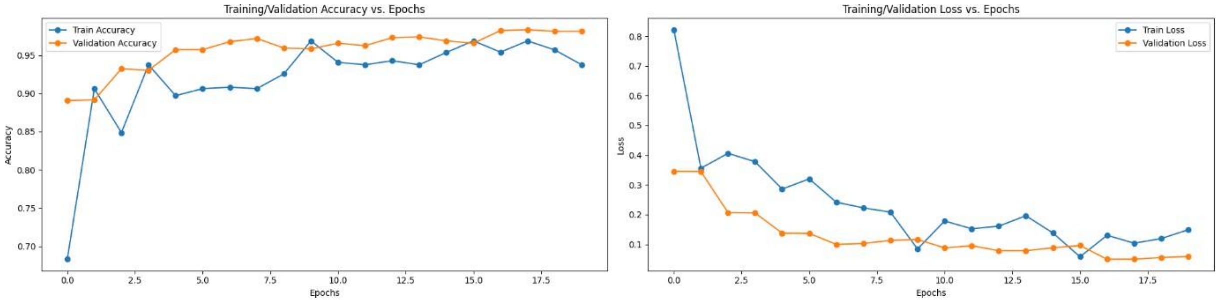

Fig 5: VGG16 training and accuracy curve

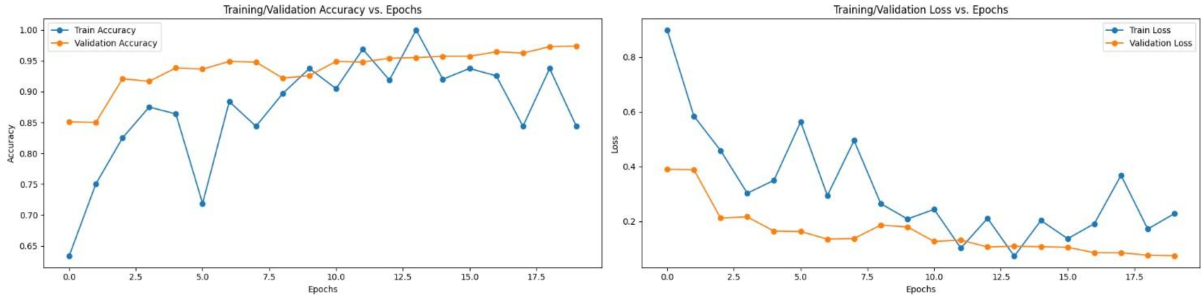

Fig 6: VGG19 training and accuracy curve

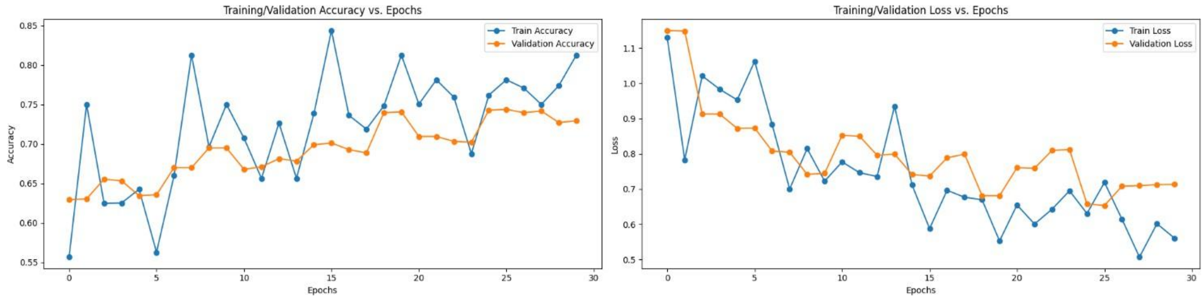

Fig 7: ResNet50 training and accuracy curve

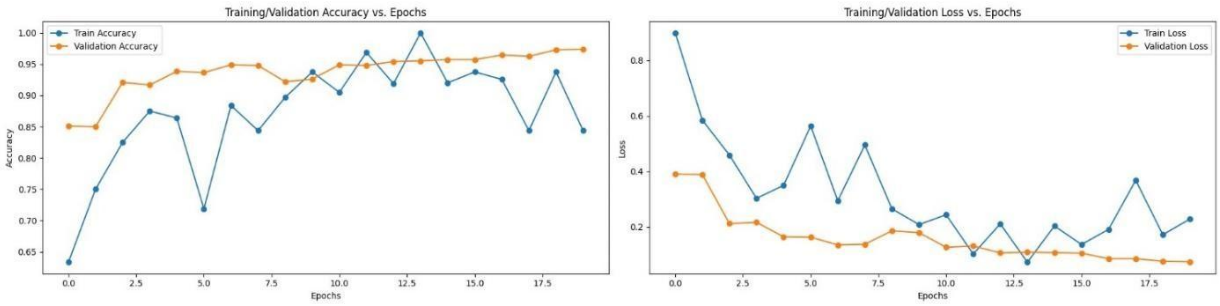

Fig 8: InceptionV3 training and accuracy curve

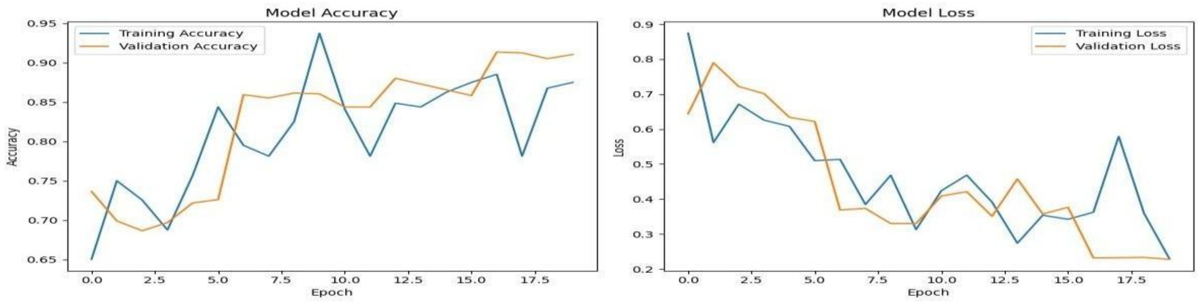

Fig 9: AlexNet training and accuracy curve

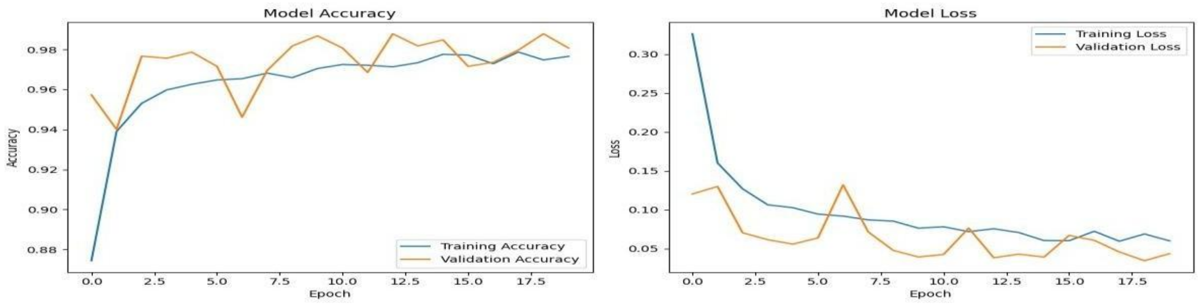

Fig 10: DenseNet training and accuracy curve

4. REFERENCES

[1] Shoaib, Muhammad, et al. "Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease." Frontiers in plant science 13 (2022): 1031748.

[2] Mathew, Midhun P., et al. "Development of a handheld GPU-assisted DSC-TransNet model for the real-time classification of plant leaf disease using deep learning approach." Scientific Reports 15.1 (2025): 3579.

[3] Schreinemachers, P.; Simmons, E.B.; Wopereis, M.C. Tapping the economic and nutritional power of vegetables. Glob. Food Secur.2018, 16, 36–45.

[4] Zhang, Keke, et al. "Can deep learning identify tomato leaf disease?" *Advances in multimedia* 2018.1 (2018): 6710865.

[5] R. Caruana, D. L. Silver, J. Baxter, T. M. Mitchell, L. Y. Pratt and S. Thrun, learning to learn: knowledge consolidation and transfer in inductive systems, 1995.

[6] Ricardo Ribani and Mauricio Marengoni. 2019. A Survey of Transfer Learning for Convolutional Neural Networks. 2019 32nd SIBGRAPI Conference on Graphics,Patterns and Images Tutorials (SIBGRAPI-T) (2019). DOI:https://doi.org/10.1109/sibgrapi-t.2019.00010

[7] Gupta, Sanjeev, and Ashish Mishra. "Deep transfer learning-based classification of White Blood Cells using customized classification base." In Proceedings of the 2024 Sixteenth International Conference on Contemporary Computing, pp. 585-595. 2024.

[8] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

[9] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016

[10] Szegedy, Christian, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. "Rethinking the inception architecture for computer vision." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818-2826. 2016.

[11] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Advances in neural information processing systems* 25 (2012).

[12] Huang, Gao, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger. "Densely connected convolutional networks." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700-4708. 2017.

[13] https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset

[14] Bhagat, Sandesh, Manesh Kokare, Vineet Haswani, Praful Hambarde, Trupti Taori, P. H. Ghante, and D. K. Patil. "Advancing real-time plant disease detection: A lightweight deep learning approach and novel dataset for pigeon pea crop." Smart Agricultural Technology 7 (2024): 100408

[15] Zhang, Tianxiang, Yuanxiu Cai, Peixian Zhuang, and Jiangyun Li. "Remotely sensed crop disease monitoring by machine learning algorithms: A review." Unmanned Systems 12, no. 01 (2024): 161-171

[16] O'Halloran, Tony, George Obaido, Bunmi Otegbade, and Ibomoiye Domor Mienye. "A deep learning approach for Maize Lethal Necrosis and Maize Streak Virus disease detection." Machine Learning with Applications 16 (2024): 100556

[17] Islam, Md Manowarul, Md Abdul Ahad Adil, Md Alamin Talukder, Md Khabir Uddin Ahamed, Md Ashraf Uddin, Md Kamran Hasan, Selina Sharmin, Md Mahbubur Rahman, and Sumon Kumar Debnath. "DeepCrop: Deep

learning-based crop disease prediction with web application." Journal of Agriculture and Food Research 14 (2023): 100764

[18] Trinh, Dong Cong, Anh Tuan Mac, Khanh Giap Dang, Huong Thanh Nguyen, Hoc Thai Nguyen, and Thanh Dang Bui. "Alpha-EIOU-YOLOv8: an improved algorithm for rice leaf disease detection." AgriEngineering 6, no. 1 (2024): 302-317.

[19] Bonkra, Anupam, Sunil Pathak, Amandeep Kaur, and Mohd Asif Shah. "Exploring the trend of recognizing apple leaf disease detection through machine learning: a comprehensive analysis using bibliometric techniques." Artificial Intelligence Review 57, no. 2 (2024): 21.

[20] Wang, Xuewei, and Jun Liu. "Vegetable disease detection using an improved YOLOv8 algorithm in the greenhouse plant environment." Scientific Reports 14, no. 1 (2024): 4261.

[21] Fu, Xueqian, Qiaoyu Ma, Feifei Yang, Chunyu Zhang, Xiaolong Zhao, Fuhao Chang, and Lingling Han. "Crop pest image recognition based on the improved ViT method." Information Processing in Agriculture 11, no. 2 (2024): 249-259.

[22] Chen, Junde, Jinxiu Chen, Defu Zhang, Yuandong Sun, and Yaser Ahangari Nanehkaran. "Using deep transfer learning for image-based plant disease identification." Computers and electronics in agriculture 173 (2020): 105393.

[23] Zayani, Hafedh Mahmoud, Ikhlass Ammar, Refka Ghodhbani, Albia Maqbool, Taoufik Saidani, Jihane Ben Slimane, Amani Kachoukh et al. "Deep learning for tomato disease detection with yolov8." Engineering, Technology & Applied Science Research 14, no. 2 (2024):13584-13591.

[24] Amrani, Abderraouf, Dean Diepeveen, David Murray, Michael GK Jones, and Ferdous Sohel. "Multi-task learning model for agricultural pest detection from crop-plant imagery: A Bayesian approach." Computers and electronics in agriculture 218 (2024): 108719.

[25] Najim, Mohammed Hussein, Salwa Khalid Abdulateef, and Abbas Hanon Alasadi. "Early detection of tomato leaf diseases based on deep learning techniques." Int J Artif Intell 13, no. 1 (2024): 509-515.

[26] Lee, Yong-Suk, Maheshkumar Prakash Patil, Jeong Gyu Kim, Seong Seok Choi, Yong Bae Seo, and Gun-Do Kim. "Improved tomato leaf disease recognition based on the YOLOv5m with various soft attention module combinations." Agriculture 14, no. 9 (2024): 1472.

[27] Saraswat, Shipra, Pooja Singh, Manoj Kumar, and Jyoti Agarwal. "Advanced detection of fungi-bacterial diseases in plants using modified deep neural network and DSURF." Multimedia Tools and Applications 83, no. 6 (2024): 16711-16733.

[28] Parasa, Gayatri, Mrs M. Arulselvi, and Shaik Razia. "Identification of diseases in paddy crops using CNN." (2024).

[29] Demilie, Wubetu Barud. "Plant disease detection and classification techniques: a comparative study of the performances." Journal of Big Data 11, no. 1 (2024): 5.

[30] Mamatov, Narzillo, Malika Jalelova, Boymirzo Samijonov, and Abdurashid Samijonov. "Algorithm for extracting contours of agricultural crops images." In ITM Web of Conferences, vol. 59, p. 03015. EDP Sciences, 2024.

[31] Barman, Utpal, Parismita Sarma, Mirzanur Rahman, Vaskar Deka, Swati Lahkar, Vaishali Sharma, and Manob Jyoti Saikia. "Vit-SmartAgri: vision transformer and smartphone-based plant disease detection for smart agriculture." Agronomy 14, no. 2 (2024):327.

[32] Abouelmagd, Lobna M., Mahmoud Y. Shams, Hanaa Salem Marie, and Aboul Ella Hassanien. "An optimized capsule neural networks for tomato leaf disease classification." EURASIP Journal on Image and Video Processing 2024, no. 1 (2024): 2.

[33] Kalpana, Ponugoti, and R. Anandan. "A Capsule Attention Network for Plant Disease Classification." Traitement du Signal 40, no. 5 (2023).

[34] Zhang, Xin, Yuxin Mao, Qi Yang, and Xuyang Zhang. "A plant leaf disease image classification method integrating capsule network and residual network." IEEE Access (2024).

[35] Abd Algani, Yousef Methkal, Orlando Juan Marquez Caro, Liz Maribel Robladillo Bravo, Chamandeep Kaur, Mohammed Saleh Al Ansari, and B. Kiran Bala. "Leaf disease identification and classification using optimized deep learning." Measurement: Sensors 25 (2023): 100643.

[36] Alkanan, Mohannad, and Yonis Gulzar. "Enhanced corn seed disease classification: leveraging MobileNetV2 with feature augmentation and transfer learning." Frontiers in Applied Mathematics and Statistics 9 (2024): 1320177.

[37] Rezaei, Masoud, Dean Diepeveen, Hamid Laga, Michael GK Jones, and Ferdous Sohel. "Plant disease recognition in a low data scenario using few-shot learning." Computers and electronics in agriculture 219 (2024): 108812.

[38] Xu, Peng, Lixia Fu, Kang Xu, Wenbin Sun, Qian Tan, Yunpeng Zhang, Xiantao Zha, and Ranbing Yang. "Investigation into maize seed disease identification based on deep learning and multi-source spectral information fusion techniques." Journal of food composition and analysis 119 (2023): 105254.

[39] Sheikh, Mansoor, Farooq Iqra, Hamadani Ambreen, Kumar A. Pravin, Manzoor Ikra, and Yong Suk Chung. "Integrating artificial intelligence and high-throughput phenotyping for crop improvement." Journal of Integrative Agriculture 23, no. 6 (2024): 1787-1802.

[40] Argüeso, David, Artzai Picon, Unai Irusta, Alfonso Medela, Miguel G. San-Emeterio, Arantza Bereciartua, and Aitor Alvarez-Gila. "Few-Shot Learning approach for plant disease classification using images taken in the field." Computers and Electronics in Agriculture 175 (2020): 105542.

[41] Ngugi, Habiba N., Absalom E. Ezugwu, Andronicus A. Akinyelu, and Laith Abualigah. "Revolutionizing crop disease detection with computational deep learning: a comprehensive review." Environmental Monitoring and Assessment 196, no. 3 (2024): 302.

[42] Mendoza-Bernal, Jose, Aurora Gonzalez-Vidal, and Antonio F. Skarmeta. "A Convolutional Neural Network approach for image-based anomaly detection in smart

agriculture." Expert Systems with Applications 247 (2024): 123210.

[43] Kamilaris, Andreas, and Francesc X. Prenafeta-Boldii."A review of the use of convolutional neural networks in agriculture." The Journal of Agricultural Science 156, no. 3 (2018): 312-322.