Deep Learning-Driven Plant Disease Identification

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by

Osama Mustafa
(2K22/DSC/09)

Under the supervision of

Dr. Abhilasha Sharma
Assistant Professor, Department of Software Engineering,
Delhi Technological University

Department of Software Engineering

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Bawana Road, Delhi - 110042, India

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

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I Osama Mustafa hereby certify that the work which is being presented in the thesis entitled "Deep Learning-Driven Plant Disease Identification" in partial fulfilment of the requirements for the award of the Degree of Master of Technology in Data Science, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from 2022 to 2024 under the supervision of Dr. Abhilasha Sharma.

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Shahbad Daulatpur, Main Bawana Road, Delhi-42

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Abhilasha Sharma

Dr. Abhilasha Sharma
Assistant Professor
Department of Software Engineering
Delhi Technological University

Date: 27/05/2024

Deep Learning-Driven Plant Disease Identification
Osama Mustafa

ABSTRACT

Plant diseases pose a significant threat to agriculture, making early and accurate detection crucial for maintaining sustainable farming practices. This study introduces an innovative solution by leveraging the advanced capabilities of the Swin Transformer V2 architecture to detect plant diseases. Moving beyond traditional methods, the research explores novel approaches in deep learning, focusing on the Swin Transformer V2's transformative potential. Utilizing the comprehensive Plant Village dataset, the dataset is meticulously fine-tuned and adapted to optimize the performance of the Swin Transformer V2. The model's development is a deliberate and thorough process, ensuring its practical applicability in real-world agricultural scenarios. Through systematic training and rigorous evaluation, the model achieves a remarkable accuracy of 98.2%, surpassing existing models. This significant achievement underscores the model's robustness and effectiveness in identifying plant diseases. The research not only enhances the capabilities of plant disease detection systems but also highlights the transformative impact of advanced deep learning algorithms on sustainable agriculture. By improving disease detection, this study contributes to global food security, showcasing the vital role of cutting-edge technology in addressing agricultural challenges and promoting sustainable farming practices worldwide.

Keywords: Plant disease detection, Swin transformer V2, neural networks, precision farming techniques, PlantVillage, advanced image recognition

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

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2K22/DSC/09

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LIST OF ABBREVIATIONS

DL	Deep Learning
ML	Machine Learning
Vit	Vision Transformer
VGG	Visual Geometry Group
GAN	Generative Adversarial Network
ResNet	Residual Neural Network
RBM	Restricted Boltzmann Machine
CNN	Convolution Neural Networks
RNN	Recurrent Neural Networks
GPU	Graphics Processing Unit
EDA	Exploratory Data Analysis
DNN	Deep Neural Networks
ANN	Artificial Neural Networks
ReLU	Rectified Linear Unit

CHAPTER 1

INTRODUCTION

1.1 Overview

Accurate detection of plant diseases is undoubtedly very important in agricultural practice. The ability to detect diseases in farming practice serves to a great extent in preventing crop loss and thereby saving food security through the optimization of resources usage [1]. Traditional methods are valuable but often fail to give pinpoint precision in their diagnoses and they bring out financial setback paybacks to the farmers [2].

This issue has, in part, been addressed by the increasing rate of technology adoption. Basically, effective pattern recognition is what deep learning techniques work well on. This forms an opportunity to just change the existing paradigm of plant disease detection systems. Nevertheless, this present paradigm is grounded mainly on single-model architectures that may find it difficult to adapt to the multifaceted challenges presented by both heterogeneous crops and varying environmental conditions, as well as the manifold of diseases affecting agricultural yield. In view of this limitation, a critical review of state-of-the-art techniques is required for enhancing the accuracy and effectiveness with which the detection of plant diseases can be improved. The Swin Transformer V2 is one of the research directions and probably one of the directions in such a limitation can be overcome with a single-model architecture among many others [5]. The most likely consideration that has gone into implementing a hierarchical design for Swin Transformer V2 is to achieve good quality models by capturing contextual information [6]. In this sense, the results tried to take advantage of its potential to obtain accurate and agile predictions of heterogeneous agricultural landscapes. The Swin Transformer V2 is quite unique and proper for plant disease recognition, showing the radical difference from the traditional single-model architecture. This paper is going to provide new knowledge in improving plant disease detection systems via comprehensive preparation of dataset, preparation of model configuration, and performance evaluation.

The model starts by preparing a comprehensive dataset sourced from the already existing Plant Village dataset, comprising images of various diseases of tomatoes, pepper, potato, and their healthy states. All classes in the dataset are clearly identified, fine-tooth combed in preprocessing for optimization of compatibility with the model. Such a classification amalgamation and preprocessing provide a very efficient handle on the features that are so important for studies of relevance to this paper.

Following dataset preparation, setting up the Swin Transformer V2, installations of dependencies, and tuning of parameters are done for optimum performance. The data pre-processing stage will involve constricting images to the size needed by the model's input, applying compatible data augmentation on it, and ensuring that they fit great with the actual conditions in agriculture.

Fig. 1.1 Sample Image of infected plant[8]

In other words, a dataset needs to be split into validation and training datasets in order to train the Swin Transformer V2. In this respect, therefore, the initialization of the model should be while monitoring and adjusting set factors put in place for the best results. For example, evaluation includes calculating metrics such as accuracy, precision, and sensitivity, which are helpful in determining the model's efficacy. The augmentation step actually does change parameters, either to get improved variety or to match parameters for the best training of the model.

As evidentially seen above, performance-wise, the Swin Transformer V2 has outperformed way ahead of the previous models like MobileNetV3, ResNet50, ViT, etc. [9], [10]. The individual class-wise accuracy, precision, recall metrics throw more light on the model's ability to provide effective predictions in detecting specific plant diseases [11].

This all points towards proving the benefits of using enhanced deep learning architectures in effective methods for plant disease diagnosis that align with Swin Transformer V2. Therefore, the research work is bound to shed more light on the improved levels of accuracy, efficiency, and real-world applicability in plant disease detection systems through meticulous preparation of datasets, performance evaluations, and model configurations.

1.2 Problem Statement

The current study is an effort to address the challenge of detecting plant diseases in agriculture in real time and accurately answering the daily dilemmas experienced by farmers across the globe. Traditional methods for disease identification are not efficient for numerous plant diseases that imperil crop yields. Drawing from state-of-the-art Swin Transformer V2 architecture [5], known for the effectiveness toward capturing fine-grained features important for precise detection of diseases, this research will contribute to at least the first step toward a solution in line with practical challenges encountered every day on the farm. The objective of this project is to provide farmers with state-of-the-art tools that could increase their capacity for prompt detection and timely response to incidences of plant diseases, as well as integrate them into sustainable and resilient agricultural practices. By virtue of surpassing the performance metrics of widely acknowledged models worldwide in the field [6], the Swin Transformer V2 promises to unlock tremendous potential. It can fuel the promise of turning farmers into real-time data-driven decision-makers for global food security [5]. This describes potential applications in agriculture and also represents improvements in techniques in making identifications of plant diseases.

1.3 Motivation

The motivation behind conducting this research project is a critical need to improve plant disease detection in agriculture — an area where accuracy and timely paramount. Traditional methods of diagnosing plant diseases, are useful, but fall to short in giving accurate and timely results, resulting in huge crop losses and Financial woes to the farmers With food security and optimization of resources, more reliable and efficient detection systems are urgently needed. Integration of advanced technologies, in particular deep-learning techniques, offers a solution with a promising view to overcome the limitations of conventional methods. By Involving the latent power of the built-in pattern recognition capabilities in deep learning, this The aim of this research is to revolutionize the way plant diseases are detected and, in turn, protection of food productivity and economic stability.

The potential of the Swin Transformer V2 to address the many-faceted challenges in detecting plant diseases. Current single-model Architectures very often struggle to accommodate the great diversity and complexity of the agricultural: Environments that fluctuate over a continuum of crops and diseases. Swin The Transformer V2, with its hierarchical design and the capability to capture rich contextual information, as it provides an enhanced option capable of improving the accuracy and robustness of the disease detection systems. This study tries to uncover and validate the potential of Swin Transformer V2 with a focus on comprehensive dataset preparation model configuration and performance evaluation to arrive at a feasible and efficient solution it outperforms the traditional models. By advancing the capabilities of plant disease detection that will bring substantial contribution to the field of agriculture,technology, providing fresh understanding and practical solutions for real-life applications.

CHAPTER 2

LITERATURE REVIEW

The field of plant illness classification has changed as a result of the incorporation of varied datasets and advanced deep-learning methods. Scientists have worked hard to improve the precision and effectiveness of algorithms used to classify plant illnesses. In the section that follows, conducting a thorough analysis of the body of research in the area and offer insights into the most recent advancements and classification techniques used for plant illness.

Table 2.1 Literature Survey

S. No	Author	Model Used	Datasets	Outcomes
1.	Baofang Chang et al.(2023) [13]	Swin,VIT, PVT	Paddy, Wheat, Cabbage, and Coffee(kaggle)	EFG excels: Paddy 97%, Wheat 98.3%, Cabbage 99.5%, surpassing competitors; Coffee exceeds 80%.
2.	Ishita Bhakta et al. (2023) [14]	VGG-16, VGG-19, Resnet50 and Resnet101	Private Dataset	Resnet50 predicts with 96% accuracy, VGG-16 and VGG19 both achieve 94% accuracy.
3.	Anwar Abdullah et al. (2022) [15]	CNN, VGG 16	Plant Village dataset	The model attained 95.2% accuracy with an overall loss of 0.4418.
4.	SUNIL C. K. et al. (2022) [16]	EfficientNetV2, Convolution Neural Network (CNN)	Plant Village (Grapes)	EfficientNet: Cardamom 94.10%, Grape 97.81%; EfficientNetV2-L: Cardamom 98.26%, Grape 96.45%
5.	Ruchi Gajjar et al. (2022) [17]	CNN, AlexNet, DenseNet, SqueezeNet	PlantVillage dataset and Private dataset	With 96.88% accuracy, the suggested model beats AlexNet (95.53%), DenseNet (96.59%)

				and SqueezeNet (94.67%).
6.	Junde Chen et al. (2022) [18]	MobileNet V2, Spatial pyramid pooling (SPP)	PlantVillage dataset	The suggested MobileNet, SPP has achieved a training reliability of 99.87% and 98.63% respectively.
7.	Sophia Chulif et al. (2022) [19]	Herbarium–Field Triplet Loss Network (HFTL network), Inception-v4, Inception-ResNet-v2	PlantCLEF 2020, PlantCLEF 2021	Method excelled in the challenging test set, achieving MRR scores of 0.108 and 0.158 in Plant CLEF 2020 and 2021—setting the largest benchmark in cross-domain plant identification.
8.	Sunil S. Harakannanavar a et al. (2022) [20]	Support Vector Machine (SVM), KNN, CNN	PlantVillage (tomato leaf)	On samples of tomato disorders, the proposed model outperformed K-NN (97%), CNN (99.6%) and SVM (88%)
9.	G. K. V. L. Udayananda et al. (2022) [21]	DenseNet-121 model, SE-ResNet-50 model, ResNeSt-50 model	Rice_disease dataset	Overall accuracy of 91% was achieved
10.	Ruoling Deng et al. (2022) [22]	SE-ResNet-50, ResNeSt-50, DenseNet-121 model	Rice disease dataset	This all yielded an average accuracy rate of 91%.
11.	YibinWang, HaifengWang et al. (2021) [23]	ADSNN-BO model, Mobile Net model	Public_rice disease dataset kaggle	Accurate test achieved with the ADSNN-BO model was 94.65
12.	Krishnamoorthy Na et al. (2021) [24]	InceptionResNetV2, CNN	Google images	CNN model fine-tuned simply with the help of a set of hyperparameters established by 15 epochs of running in order to attain an accuracy rate of 84.75%.
13.	Punam Bedi et al. (2021) [25]	CNN, VGG16	Kaggle dataset with 1600 images	VGG16 with training accuracy of 100% and test accuracy of 60% The dataset was derived

				from academics accuracy value of 60%
14.	Rasim Alguliyev et al. (2021) [26]	CNN + GRU , ResNet-20 , VGGNet-16	PlantVillage dataset	Accuracy of CNN + GRU is 90.88, accuracy of ResNet-20 is 91.76, accuracy of VGGNet-16 is 96.05
15.	I Y Purbasari et al. (2021) [26]	CNN, multilayer perception (MLP)	Plant Village (2239 image of each type)	Research achieves automated leaf disease detection with best training accuracy at 91%.
16.	M. S. Mustafa et al. (2020) [27]	Fuzzy inference system, naive Bayes (NB), probabilistic neural network (PNN) and SVM classifier	Leafsnap dataset, Flavia dataset, ICL dataset	SVM accuracy: 97.9, PNN accuracy: 98.5, Naive Bayes accuracy: 94.6. Combined SVM + PNN + NB + FIS achieves 98.4%.
17.	Muammer TÜRKOĞLU 1 et el. (2019) [28]	Support vector machine, KNN, Extreme learning machine (ELM), AlexNet	In the field of plant protection at Agricultural Faculty of Bingöl University and İnönü University, Turkey.	ResNet50 with SVM achieved the highest accuracy at 97.86%. SVM classification also resulted in high accuracies: GoogleNet (95.22%), InceptionV3 (94.96%), and SqueezeNet (95.62%).
18.	Zhongqi Lin et al. (2019) [29]	CNN, matrix-based convolutional neural network (M-bCNN)	16,652 pictures of high resolution were captured from various wheat planting regions in Shandong province and marked as the original image data	Added to this fact is that concerning data, M-bCNN obtained a validation accuracy as high as 96.5% and testing accuracy of 90.1%. In this way, it outperforms AlexNet and VGG-16.

The following are some of the key takeaways from the preceding table:

1. Data augmentation has shown to be a highly successful strategy for improving overall performance and making the model more resilient to noise.

2. Oversampling strategies for adjusting for uneven numbers of entities increase performance in classes with unequal numbers of entities.

3. For image classification tasks, DL models are more accurate than machine learning models.

4. The classification accuracy improves as the number of photos per class used to train the models grows.

5. After achieving a particular high degree of accuracy, expanding the model's complexity to better suit the job yields decreasing returns.

6. When the model is trained for a small number of epochs (less than 20), the model frequently does not acquire enough features from the input to correctly categorize the test pictures.

7. The main advantage of using DL Technique instead of ML Technique is that DL does Feature Extraction and Classification by itself but in ML we do Feature Extraction Manually.

CHAPTER 3

RESEARCH GAPS

1. **Generalizability and Transferability of Models**
   There is a significant gap in making disease identification models that can be effectively applied across various crops and environmental conditions. Many models are trained on specific datasets, limiting their broader applicability. Future work should focus on enhancing the generalizability of these models through diverse datasets and the use of transfer learning techniques..

2. **Real-Time Detection and Computational Efficiency**
   Achieving real-time detection of plant diseases while maintaining computational efficiency is still a challenge. While models like Faster R-CNN and YOLO show promise, they need further optimization to handle real-time processing without significant computational overhead. Efforts should be made that sought to strike a balance between speed and accuracy for practical purposes.

3. **Integration of Multidisciplinary Data**
   multi-disciplinary data, including the meteorological conditions, soil data, and Plant traits are incorporated into disease detection models to a very minimal degree. This Additional information can greatly help in increasing thecomprehensiveness of these systems. Future research should be directed toward creating models that take a wider variety of data input. Training sets that are annotated and diverse will be available are currently limited. They can be improved with various plant diseases and Conditions under such diseases as cardamom, with nutritional deficiencies, get very critical. Enlarging datasets by diversification will enhance the quality of training datasets and Validation procedures.

4. **Dataset Augmentation and Enhancement**
   As a consequence, many current models are complex and/or have a large parameter set, hence often making the processing time slow and thus impractical. This is exactly where approaches like network pruning come into the picture: reducing complexity or size in a network to improve speed and overall efficiency in a method. Future work needs to be focused on optimal tuning of model hyper-parameters to strike a balance between performance and computational demand.

5. **Model Complexity and Parameter Optimization**
   Most of the current models are overparameterized and very complex, which results in processing delays and hence slower practical application. The techniques to be adopted in making learning efficient are those of reducing complexity through network pruning. Future work should focus on model

parameter optimization that leads to a good performance with manageable computational demands.

6. **Advanced Model Architectures**
   Important areas that need to be explored further are the refinement of state-of-the-art architectures, such as Vision Transformers (ViTs) and Generative Adversarial Networks (GANs), for better performance in plant disease identification. The primary research concern is how best the use of these state-of-the-art deep learning models can be employed for higher accuracy and robustness using hybrid attention mechanisms.

7. **Cross-Species and Cross-Condition Performance**
   Very few studies have been conducted on performance under different plant species and environmental conditions. Extending these models to various crops and plants could ensure robustness and dependability in diversified agricultural settings, hence making them very versatile and us

8. **Standardization and Benchmarking**
   Another important factor for consistent evaluation and comparison is the non-existence of standardized protocols and benchmarks for plant disease identification models and their evaluations. Development of standardized datasets, metrics, and protocols supports consistency in evaluation and comparison activities that make the activity of creating open worldwide herb recognition and diagnosis models.

In such areas of gaps, they validate research much more than the current limitations and drive the field towards truly advanced and applicable solutions in computer vision approaches. By meeting these demands, it will be possible to improve theoretical understanding and practical application of machine learning and image classification technologies.

CHAPTER 4

METHODOLOGY

The paper seeks to further develop the field of plant disease classification and recognition through using the Swin Transformer V2 with all of the PlantVillage dataset. The importance of accurate disease identification in agriculture drives a systematic approach toward cutting-edge performance [28]. The setup has been done critically for maximum special qualities, stressing maximum strength and durability in categorizing ill plants. The model will be properly trained on the categorized PlantVillage dataset, well-arranged with different classes, each belonging to a particular plant disease. Model training and testing are done rigorously with important metrics, such as model accuracy, precision, and sensitivity. The comparison analysis showed that Swin Transformer V2 works great in handling the diversities in plant diseases and stresses its applicability in real agricultural scenarios.

4.1 Proposed Work

1. Design a generalized framework based on Swin Transformer V2 architecture [7] for plant disease detection and classification in one shot. This paper emphasizes optimization for amalgamating the results of models [12].

2. Aggregate a diverse dataset encompassing several types of plant diseases, crop types, and a wide range of environmental conditions. This dataset was then used to train the model based on the Swin Transformer V2 for data augmentation directed at attribute refinement [14].

3. Perform full tests on sufficient datasets in proper agricultural conditions. The F1-score method also helps validate the within-limits amounts, if found useful for an effective task in an ensemble model based on Swin Transformer V2 for use in plant disease detection [15].

4. Evaluate the Swin Transformer V2-based ensemble model under performance in scenarios where the environment might not be ideal due to factors like environmental conditions, changes in illumination, and potential interferences. The findings will shed light on the model's limitations and improvements associated with the constraints.

5. Advanced techniques, including data augmentation, transfer learning, and post-model refinements, are employed in enlarging the ensemble Swin Transformer V2 model for further enhancement of its performance metrics. Challenges from environment factors and any other disturbances will need to be overcome to

ensure that the results received are objective under wide-ranging different lighting conditions [16].

4.2 Implementation

Details in that regard, including the step-by-step implementation, are described below for the CNN algorithm and transfer learning techniques implemented in the project. All implementations were conducted in Python programming, using a popular deep learning framework, TensorFlow, and Keras.

First, we obtained a dataset relevant for the project, one that consists of labeled images relating to the target classification task. The dataset was split into the following: training, validation, and testing sets in proper proportions so as to ensure that model evaluation would be reliable.

4.2.1 Swin Transformer V2

The core of the proposed methodology is a plug-and-play state-of-the-art Swin Transformer V2, designed based on the pioneering research in Swin Transformer and its precursor, Vision Transformer. While the ViT mainly proposed the application of Transformer architectures for image categorization, subsequent works into the associated architectures and training approaches have inspired a good number of further advances [6]. Exploiting the ViT-based architecture, which relied on the hierarchy structure and the capability of shifting windows to gather information about context in global and local space, the Swin Transformer amounts to yet another breakthrough in CV [5].

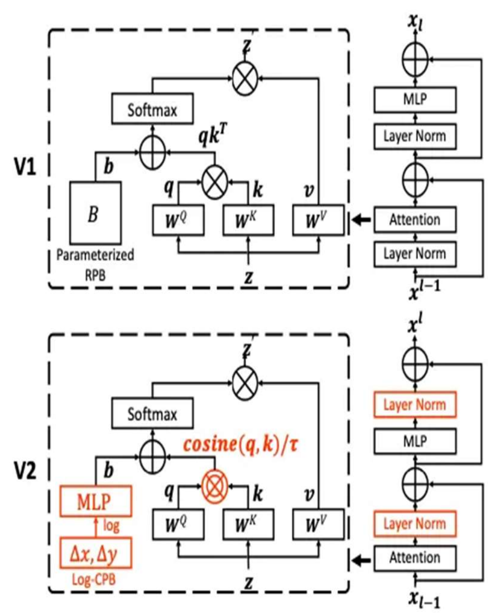

Fig. 4.1 Structure of Swin Transformer V2 [7]

It specifically tackled training instability, addressed the resolution gap for knowledge transfer, and reduced data dependency, leading to remarkable advancements [7]. With a staggering 3 billion parameter capacity, the ability to handle images up to 1536x1536 resolution, and requiring 40 times less labeled data while delivering superior performance, Swin Transformer V2 stands as a testament to continuous innovation. The outstanding stability and information effectiveness of this system can be attributed to structural improvements like residual-post-norm, cosine focus, and log-spaced ongoing position bias. Swin Transformer V2 reinforces the narrative of continuous improvement, pushing the boundaries of vision tasks and solidifying its status as a powerful and efficient vision Transformer architecture [7].

4.2.2 PROCEDURE OF PROPOSED MODEL

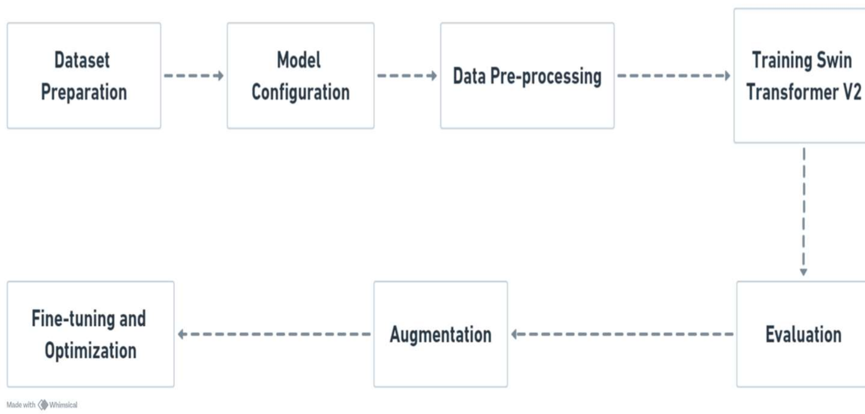

Fig. 4.2 Algorithm of Proposed Model

Dataset Preparation

1. Organize the PlantVillage dataset with distinct folders for each plant category.
2. Arrange images by classes, ensuring annotation files are available.

Model Configuration

1. Install Swin Transformer V2 dependencies.
2. Obtain Swin Transformer V2 source codes or pre-trained models.
3. Configure Swin Transformer V2 by adjusting parameters.

Data Pre-processing

1. Resize images to match Swin Transformer V2's input size.
2. Apply Swin Transformer V2-compatible data augmentations.
3. Convert annotations into the required format for Swin Transformer V2.

Training Swin Transformer V2

1. Divided the dataset from PlantVillage into sets for validation and training.
2. Initialize and train Swin Transformer V2.
3. Monitor training, adjust parameters, and assess Swin Transformer V2's performance.

Evaluation

1. Use Swin Transformer V2 for predictions on the validation or test set.
2. Calculate relevant evaluation metrics for Swin Transformer V2.
3. Visualize predictions and compare results with benchmarks.

Augmentation

1. Enhance dataset variety with Swin Transformer V2-compatible augmentations.
2. Adjust augmentation parameters for optimal model training.

Fine-tuning and Optimization

1. Fine-tune Swin Transformer V2 based on dataset specifics.
2. Explore optimization techniques, such as transfer learning or additional augmentation.
3. Iterate through fine-tuning and optimization steps.

4.2.3 Baseline Models

1. **MobileNetV3:** designed for mobile and edge devices, prioritizing efficiency and optimized model size. It combines depthwise separable convolutions with squeeze-and-excitation modules to balance performance and resource usage [9].

2. **ResNet50:** A deep convolutional neural network with 50 layers, using skip connections to mitigate the vanishing gradient problem, thereby improving training and accuracy. [28].

3. **ViT:** Treats images as token sequences, a departure from traditional convolutional approaches [6].

4. **EfficientNet:** EfficientNet scales model depth, width, and resolution using a compound scaling method, achieving high performance with efficient resource use. [29].

5. **VGG-16:** VGG-16 is a traditional CNN with 16 weight layers, known for its simplicity and effectiveness in image classification [30].

6. **InceptionV3:** Features deep convolutional architecture with inception modules for efficient multi-scale feature capture [31].

7. **RetinaNet:** Recognized for its one-stage object detection and focal loss mechanism to improve object localization [32].

8. **GoogleNet:** Also known as InceptionV1, employs inception modules, emphasizing depth and width for effective feature extraction [33].

9. **AlexNet:** A pioneering deep neural network architecture that played a pivotal role in popularizing deep learning, especially in image classification [34].

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CHAPTER 5

EXPERIMENTAL SETUP

5.1 Tools Used

- Jupyter Notebook: These find their application in so many data science tasks—some of which include exploratory data analysis, data purifying and transformation, data visualization, statistical modeling, machine learning, deep learning—but also so much more.

- Pandas: A data analysis library of Python that comes with structures and functions useful for the manipulation of collections of data. It contains tools for analyzing, cleaning, inspecting, and reshaping data. It was developed in 2008 by Wes McKinney, and the name "Pandas" comes from "Panel Data" and "Python Data Analysis".

- Matplotlib: Matplotlib is a powerful package in Python that allows one to make visualizations ranging from static to animated and interactive. It can be very easy or very hard depending on the feature you wish to implement, such as the following general points: Ready-for-publication plots. Figures that can zoom, pan, and update..

- Seaborn: Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

- Scikit-learn: One of the most useful machine learning libraries in Python. Sklearn is a package with very useful methods to perform machine learning and statistical modeling—for example, it has methods for classification, regression, clustering, and dimensionality reduction.

- TensorFlow: An open-source library by Google for developing deep learning applications and further ensuring conventional machine learning. It was developed primarily to help perform large numerical computations conducted by Google Research without necessarily considering deep learning.

The PlantVillage Dataset, often found on Kaggle, contains a comprehensive collection of images focused on plant disease. The dataset contains roughly 15,915 photos, making it an excellent resource for training and testing machine learning projects. All of the photographs depict plant disease, with a variety of disease, shape, and size designs typical of plant. Images are often delivered in standard formats such as JPEG or PNG, allowing for simple integration into machine learning pipelines and frameworks.

5.2 Experiment Configuration for Training

Table 5.1 Experiment Configuration for Training

Name	Value	Description
Training Iterations	100	Number of iterations during model training
Sample Quantity	32	Number of data samples used in each training iteration
Optimization Method	AdamW	Methodology for updating network parameter
Regularization Factor	0.05	Factor controlling model overfitting prevention
Learning Rate	0.001	Rate at which the model adjusts during optimization
Objective Function	Cross entropy	Metric assessing dissimilarity between predicted and true values
Image Dimensions	224 x 224	Dimensions of the input image for the model

CHAPTER 6

RESULTS AND ANALYSIS

6.1 Dataset

The study relies on the Plant Village dataset, comprising 15,915 images of various plant diseases. The dataset is organized into fifteen distinct classes, each representing a specific disease or a healthy state. These classes are mutually exclusive, ensuring that a single image belongs to only one class. Notably, the classes encompass diseases in tomatoes, potatoes, peppers, and healthy states. Detailed visual representations of these classes and their associated crops are depicted in Fig. 3. To optimize compatibility with the chosen model, textual values underwent conversion into numeric representations. Furthermore, 80% of the dataset's images were allocated for training, with the remaining 20% reserved for testing, ensuring a robust evaluation of the model's performance on unknown data.

Fig. 6.1 Sample dataset of PlantVillage

Classifiers for plant disease can be trained and tested over the PlantVillage dataset to ensure that these classifiers are generalizable to a broad cross-section of agricultural and environmental conditions.

Table 6.1 Distribution of Dataset

Class label	**Class Name**	**No. of Images**
0	PepperBacterialSpot	997
1	PepperHealthy	1478
2	PotatoEarlyBlight	1000
3	PotatoHealthy	1000
4	PotatoLateBlight	152
5	TomatoBacterialSpot	2127
6	TomatoEarlyBlight	1000
7	TomatoHealthy	1909
8	TomatoLateBlight	952
9	TomatoLeafMold	1771
10	TomatoSeptoriaLeafSpot	1676
11	TomatoSpiderMitesTwoSpottedSpiderMite	1404
12	TomatoTargetSpot	3209
13	TomatoMosaicVirus	373
14	TomatoYellowLeafCurlVirus	1591

6.2 Results And Discussion

We reviewed several categories of plant illness and assessed some baseline models using the large dataset from PlantVillage. This dataset contains a large number of images showing different diseases of pepper, tomato, potato crops, and other vegetable crops with their healthy conditions. The models being studied for this work are MobileNetV3, ResNet50, ViT, EfficientNet, VGG-16, InceptionV3, RetinaNet, GoogleNet, and AlexNet, with the new Swin Transformer V2. Much details such as precision, F1 score, and recall metrics of each model are detailed in Table V with much care to reveal individual capacities for precise classification and recognition of plant diseases.

Table 6.2 Different Model Comparison

Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**
MobileNetV3	97.2	0.937	0.936	0.936
ResNet50	98	0.955	0.96	0.957
ViT	97.7	0.95	0.953	0.951
EfficientNet	97.9	0.957	0.955	0.956
VGG-16	97	0.93	0.94	0.935
InceptionV3	97.8	0.953	0.957	0.955
RetinaNet	93.5	0.885	0.935	0.909
GoogleNet	97.5	0.945	0.95	0.947
AlexNet	96	0.92	0.925	0.922
Swin Transformer V2	98.2	0.97	0.975	0.972

6.3 Performance Analysis

Swin Transformer V2, on the other hand, attained an accuracy score of 98.2%, outperforming all the models from the list. This excellent result makes the Swin

Transformer V2 top in plant disease identification. This shows success in improving agricultural practices to meet the food security threshold. Nuance0ed Result Analysis: The Unique Strengths of Swin Transformer V2 and What It Portends for the Task of Plant Disease Classification.

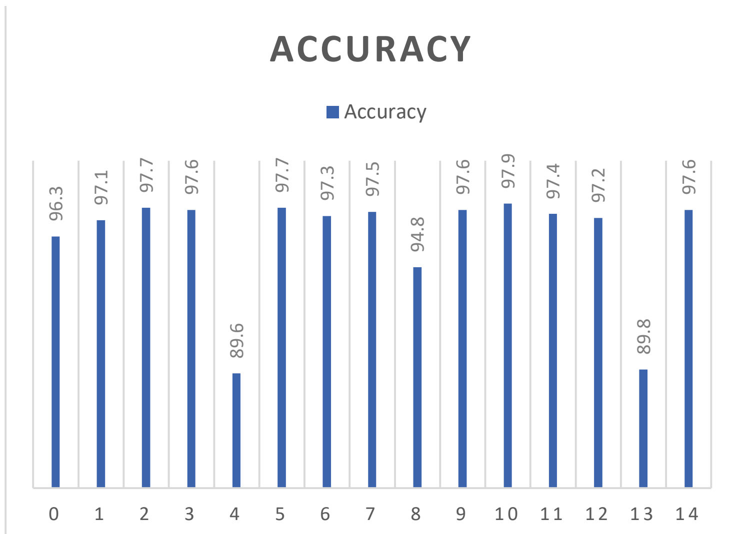

Fig. 6.2 Accuracy of different classes of Dataset using Swin Transformer V2

A reflection of this is so high accuracy, showing efficiency in very accurate prediction of crop health; thus forming a firm basis for deployment in the real agricultural settings. This very powerful tool enables farmers and other stakeholders to be interested in agriculture to move from just identifying diseases reliably to proactive disease management.

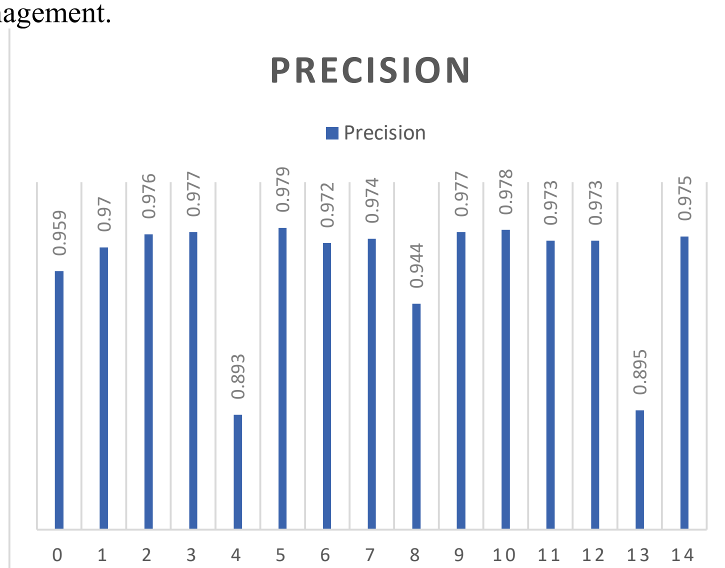

Fig. 6.3 Precision of different classes of Dataset using Swin Transformer V2

Thus, in the case of precision metrics, the Swin Transformer V2 demonstrates a high level of precision for most classes of plant diseases, from 0.893 to a remarkable score of 0.979. The power of the model is depicted by the high values of precision for Classes 2, 5, and 10, which allow minimizing the rate of error and increasing correct prediction. Such exactitude in calling specific diseases is treasured by the agricultural community where undue alarm or even misclassification can be very serious. In a way, this speaks to the model's discriminative power, which is crucial for making targeted interventions and for strategies for effective disease control.

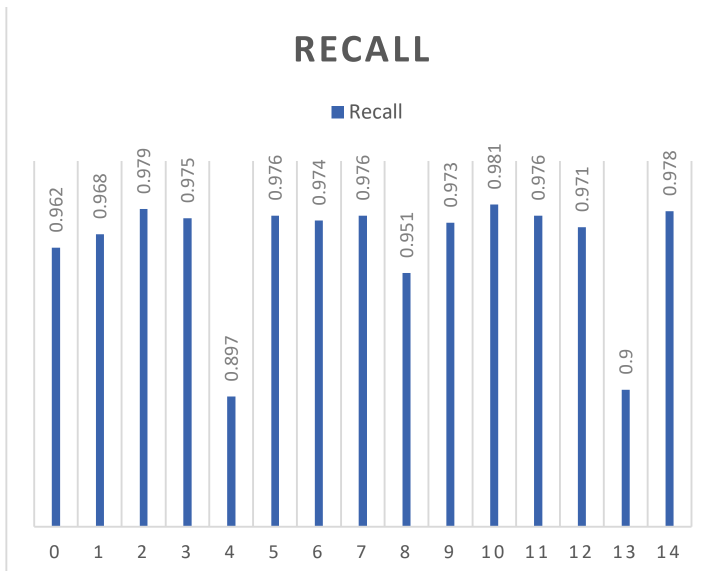

Fig. 6.4 Recall of different classes of Dataset using Swin Transformer V2

For the measure of recall, it becomes yet clearer how good Swin Transformer V2 is to catch examples of plant diseases over different classes. The recall values range from 0.897 to an outstanding 0.981, whereby the model can detect and bring out disease cases in most of the classes of various crops. Most of the classes have good recall, though with small discrepancies; only Class 4 shows slightly low recall of 0.897. This could indicate problems with the detection of diseases related to this class. The detailed analysis of accuracy, precision, and recall gives in-depth insight into the performance of Swin Transformer V2 in plant disease detection. A sophisticated tool for precision agriculture, the model goes further than just meeting the very high expectations of monitoring and management practices on crop health in modern agriculture.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

In summary, the applicability of Swin Transformer V2 in this context has showcased a noted achievement in precision agriculture. Great recall score, accuracy, and precision of the model would reveal its power for farmers to have very important information in time for the management and intervention of diseases. As one might expect for the future of this research, it will be even more effective to integrate much larger and diversified datasets to improve the model. In that way, not only the model can be strong but also be adaptable to different agricultural landscapes. Looking into state-of-the-art techniques, like transfer learning, might improve our current model, and it would allow the detection of subtle differences between different manifestations of the disease. Furthermore, research should be conducted on the design or model robustness under dynamic environmental conditions and integrated into real-time monitoring. After all, the advance of Swin Transformer V2 in this field can effectively change the scenario of disease detection and also contribute to the other major objectives of agriculture that are sustainable and driven by technology.

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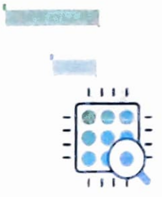

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3. Thesis title: Deep learning-Driven Plant Disease Identification
4. Degree for which the thesis is submitted: M-TECH
5. Faculty (of the University to which the thesis is submitted) Dr. Abhilasha Sharma
6. Thesis Preparation Guide was referred to for preparing the thesis. YES ☑ NO ☐
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