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An Empirical Study of Precision Agriculture

Gnana kartheek tirumalasetti
Dept of Computer science engineering
SRM UNIVERSITY AP, India
Vijayawada,Andhra Pradesh
gnanakartheek_t@srmap.edu.in

Ajay kumar Kandula
Dept of Computer science engineering
SRM UNIVERSITY AP, India
Vijayawada,Andhra Pradesh
ajaykumar_kandula@srmap.edu.in

Abdul Basheer Shaik
Dept of Computer science
SRM UNIVERSITY AP, India
Vijayawada,Andhra Pradesh
abdulbasheer_shaik@srmap.edu.in

Baladithya Yendluri
Dept of Computer science engineering
SRM UNIVERSITY AP, India
Vijayawada,Andhra Pradesh
baladithya_yenduluri@srmap.edu.in

Hemantha Kumar Kalluri
Dept of Computer science engineering
SRM UNIVERSITY AP, India
Vijayawada,Andhra Pradesh
hemanthakumar.k@srmap.edu.in

***Abstract*—The demand for food production has led to advancements in precision agriculture, aiming to enhance crop yield and quality. This study investigates the application of deep learning algorithms, including GoogLeNet, RESNET-50, MobileNet-v2, VGG-16, and ShuffleNet, for automated plant disease detection. The research utilizes a dataset comprising images of citrus diseases to train and evaluate the models. Results show promising accuracy rates, highlighting the potential of deep learning in optimizing resource utilization and facilitating timely interventions in agriculture.**

Keywords—Precision agriculture, Deep learning, Plant disease detection, Image classification, Citrus diseases.

I. INTRODUCTION

The field of image feature extraction and classification is highly relevant in precision agriculture, particularly for addressing plant diseases. Deep learning models such as GoogLeNet, ResNet-50, and MobileNet-v2 have shown significant improvements in detection accuracy and efficiency compared to traditional methods.

BACKGROUND JUSTIFICATION

Current disease detection methods rely on human visual assessment, which is time-consuming and prone to errors, especially in large-scale farming. Deep learning offers a solution by automatically learning features from raw data, reducing the need for expert intervention. However, challenges persist, including the need for extensive datasets and variability in image quality. The applicability of these models in real-world agricultural settings is still under investigation.

This study builds on these advancements by investigating automated image classification for early plant disease detection in precision agriculture. Early detection is crucial for maintaining crop quality, and current human-based methods are inadequate for large-scale farming. By leveraging advanced deep learning models such as GoogLeNet, ResNet-50, MobileNet-v2, VGG-16, and ShuffleNet, this research aims to enable timely interventions and optimize resource utilization.

Deep learning has revolutionized the field by enabling end-to-end approaches that eliminate the need for expert feature engineering. Convolutional Neural Networks (CNNs) have been central to this transformation, though they require extensive datasets for high accuracy. This paper contributes to the empirical understanding of disease detection in agriculture, highlighting the potential impact on crop health and productivity. Integrating these advanced models aims to enhance the accuracy and efficiency of plant disease detection, supporting the advancement of precision agriculture.

II. LITERATURE REVIEW

With the development of Geographic Information Systems (GIS) and Global Positioning Systems (GPS) in the late 20th century, the idea of precision agriculture first surfaced. Pioneering research by scholars like Pierre Robert and John Deere laid the foundation for precision agriculture. Initially, precision agriculture mainly focused on the management of spatial data for farm decision-making. Precision agriculture encompasses various components, including data collection through sensors and remote sensing technologies, automated machinery, and data analytics. GPS-enabled devices have significantly influenced precision agriculture, allowing for precise positioning and mapping of fields, which is vital for efficient resource management.

A major focus of precision agriculture is crop monitoring. Remote sensing technologies, including drones and satellites, have become integral for collecting data on crop health, moisture levels, and nutrient content. These technologies facilitate early disease detection, enabling timely intervention. Precision agriculture aids in the efficient use of resources such as water, fertilizers, and pesticides. Variable rate application (VRA) systems adjust the application of these resources based on real-time data, reducing wastage and environmental impacts.

The role of data analytics and machine learning in interpreting the vast amounts of data generated by precision agriculture is explored. Machine learning algorithms can analyze and make predictions based on data, leading to better-informed decisions in crop management.

Machine learning and deep learning techniques are at the forefront of precision agriculture, enhancing the efficiency and sustainability of farming practices. Here are some key approaches and methods employed in precision agriculture.

A. Crop Health Monitoring

CNNs are used to analyze remote sensing data, such as satellite and drone imagery. They can identify patterns and anomalies in crop health by examining variations in color, texture, and vegetation indices. RNNs can be applied to time-series data, tracking changes in crop health over time. They are useful for monitoring disease progression and growth stages.

The paper [2] discusses the development of a prediction system using IoT based sensor networks. Traditional soil testing labs can be slow in providing results, causing delays for farmers. This system aims to offer faster crop predictions. The focus of the paper is on analyzing soil nutrient levels, particularly Nitrogen (N), Phosphorus (P), and Potassium(K). The proposed method efficiently estimates these soil nutrients using data from the sensor network, helping predict suitable crops for the soil being tested. Farmers are required to connect their NPK sensors to a central server. These sensors extract nutrient levels from soil samples and transmit the data to the main server through Raspberry Pi units. Predictions are made based on the collected data. However, there are limitations in the crop prediction algorithm's efficiency and an overemphasis on data collection through NPK sensors, which are susceptible to significant fluctuations.

In the paper [3], a Crop Selection Method is introduced to address the challenge of crop selection and enhance overall harvest yield. The method considers various factors such as climate, soil composition, water availability, and crop type when recommending a range of crops to be cultivated during a season. The accuracy of this method relies heavily on the precise estimation of these influential factors. The approach discussed in the paper involves crop sequencing, where crops are categorized into seasonal, year-round, short-term, and long-term crops. However, there is a need for an improved prediction technique with higher accuracy, performance and a requirement for selecting at least one crop from each category, which can be a significant challenge.

The necessity of crop yield forecasts and its assistance in a country's strategic policy formulation in agriculture are stated in the study [4]. The structure stands for eXtensible Crop Yield Prediction Framework (XCYPF). developed. It permits the flexible incorporation of different methods for predicting agricultural yield. Also, a tool was created to assist individuals in forecasting agricultural productivity for diverse crops with interdependent and unbiased factors.

The paper [5] describes the application of data mining and visual data mining approaches to agricultural data. The high dimensional agricultural data in this paper is reduced to smaller scale to obtain practical yield-related knowledge, application of inputs (such as fertilizers).The methods employed include Scaling in several dimensions and self-organizing maps strategies to decrease the data (Sammon's mapping).The inference is that Self-organizing maps are appropriate. Sammon's mapping is appropriate and the dataset is huge when the dataset is tiny.

The goal of the paper [6] is to find a solution to Egypt's food insecurity issue. It offers a framework for projecting the production and imports for that particular year. It makes use of Multi-layer ANN and perceptron in WEKA to construct the forecast.

A category is predicted by analyzing and categorizing the soil datasets in paper [7]. The crop yield is classified based on the projected soil category. Rule. The KNN and Naïve Bayes algorithms are used to forecast crop yields.

A random tree [8] and a decision tree are comparable. However, it varies from random trees in that only a random subset of attributes is provided for each split. Trees at random can be constructed to handle both numeric and nominal data. The Chance Tree is comparable to C4.5 or CART, but it differs in that Prior to being used for training,it just chooses a random portion of the qualities. Every node considers K at random. Selected qualities. The parameter for subset ratio indicates the subset size.

Hybrid Approaches: Integration of Image processing and deblurring Techniques Image deblurring in precision agriculture is a critical image processing technique that plays a significant role in improving the quality and accuracy of images captured for agricultural applications. (From Reference [1]).

Lucy-Richardson Deconvolution This iterative deconvolution technique is commonly used for deblurring in microscopy and astronomical imaging. It estimates the original image from a blurred version by iteratively refining the estimate. Disease detection Techniques YOLO is an object detection algorithm, specifically the YOLO v4 version, as the core for disease detection. YOLO v4 is well known for its enhanced processing speed, excellent accuracy, and real-time identification of objects capabilities.

III. METHODOLOGY

A. Dataset

Hafiz Tayyab Rauf's dataset contains 609 images of citrus diseases. This dataset contains 5 modules: Healthy, Greening, canker, blackspot, Melanose. Citrus Canker: The disease causes a brown patch on leaves with a yellow halo surrounding it. Usually leaves have an oily or wet surface. Citrus Greening: The symptoms frequently show up as yellow veins and spots on orange tree leaves. There are erratic splotches on the damaged leaves.

Fig. 1. *Cancer*

Fig. 2. Greening

Fig. 3. Healthy Citrus Leaf

B. Plant disease detection

Plant disease detection is being addressed through a combination of traditional and deep learning-based approaches. Two different experimental setups are used.[10] First, they investigate transfer learning for texture classification using CNN models pre-trained on large object datasets. Second, they apply this approach to plant disease detection in precision agriculture.

68 different kinds of RGB textured images from the "Outex_TC_00013" dataset are used to test the proposed method. Each class has twenty 128x128 pixel samples, for a total of 1360 images. The little diversity across classes and the tiny number of samples per class make the dataset difficult to work with.

For plant disease detection, the "Plant Village" dataset is utilized, containing images of various plant species, some healthy and some affected by diseases.

C. Image classification:

After feature extraction, a neural network is used to classify the images in the learning database.In this context, the feature vectors serve as neurons within the artificial neural network (ANN) described in reference [17]. The neuron's output is determined by a weighted sum of its inputs. Various techniques like the backpropagation algorithm, adapted like SOM and Multiclass Vector Machines can be applied for this purpose.
For image classification [11] they used pre-Defined CNN models from which a feature vector is obtained. SVM is a traditional machine learning technique that can be used for image classification. It works well when you have extracted features from images, The authors employed the SVM with RBF kernels as supervised classifiers.
Deep Learning techniques can be used for plant disease detection:

a) *Efficient with K-Fold Cross-Validation:*
The machine learning approach combines the power of EfficientNet, a deep neural network model, with K-Fold Cross-Validation, a technique for model evaluation.
Convolutional neural network models in the EfficientNet family scale with respect to depth, breadth, and resolution. These models are engineered to achieve state-of-the-art performance in a variety of computer vision applications while making optimal use of computational resources. The model is trained and verified K times using the K-Fold Cross-Validation validation approach, utilizing one fold as the validation set and the remaining fold as the training set. There are K folds, or subsets, inside the dataset. Together, EfficientNet and K-Fold Cross-Validation provide quick training and assessment of the model on various dataset subsets, hence enhancing the model's robustness and generalization.

b) *EfficientNet:*
It is among the deep learning models that Google created in 2019. It is intended to be computationally efficient while achieving cutting-edge performance. The fundamental principle of EfficientNet is to use a compound scaling mechanism to grow the network's resolution, depth,and width simultaneously.Depth-wise, width-wise, and resolution-wise scaling are used to adapt the model's architecture to different input sizes and computational resources.
The model's parameters are controlled by coefficients α, β, and γ, which are determined through a grid search (coefficient ϕ). EfficientNet models range from B0 (smaller and faster) to B7 (larger and more accurate), with each model handling higher-resolution images.

c) *Feature Extraction:*
AlexNet's convolutional layers are used as a feature extractor. When a textured image is input into AlexNet, the network processes the image through its convolutional layers, capturing hierarchical features and textures. These features are then used to represent the image in a feature vector.

d) *DenseNet:*
IThis has a dense network connecting every tier. One convolution layer and one pooling layer follow each dense block. There must be more layers in this in order to improve accuracy. However, the issue of diminishing gradient arises after a certain number of layers.

e) *VGG-19:*
The VGG-19 model consists of nineteen layers in total, including sixteen convolutional layers. Among these layers, there are five pooling layers. Following the first two layers, the second pooling layer is introduced. Subsequently, the third pooling layer follows after four layers, the fourth after eight layers, and the fifth after twelve layers. Finally, there is a softmax layer, and the last three layers before the softmax are fully connected layers.

f) *Resnet50 And SVM Classifier:*
Resnet50: ResNet50 is a deep neural network comprising 50 layers, with "ResNet" standing for "Residual Network." This architecture draws inspiration from VGG-19 and addresses the vanishing gradient problem by incorporating shortcut connections. It consists of 48 convolution layers, one layer of max pooling, and one layer of average pooling. A notable drawback of ResNet is its susceptibility to the vanishing gradient issue, which is mitigated using skip connections. These skip connections involve bypassing several connections directly, resulting in a different output compared to when connections are not skipped.

IV. EXPERIMENTAL RESULTS

The MATLAB implementation code runs on a PC equipped with a Windows operating system, an Intel Core i5 processor clocked at 3.2 GHz, and 8 GB of RAM.

Models	No.of layers	Input image size	Accuracy
GoogLeNet	22	224x224x3	95.52%
RESNET-50	50	224x224x3	97.01%
MobileNet-v2	53	224x224x3	92.54%
VGG-16	16	224x224x3	34.33%
ShuffleNet	50	224x224x3	95.52%

TABLE 1. ACCURACY OBTAINED USING VARIOUS DEEP LEARNING MODELS.

A. GoogLeNet

In this study we used the GoogLeNet architecture which contains 22 layers in MATLAB’s Deep Network Designer to create a reliable model for plant disease detection. The model was trained on a dataset of 609 images in 5 folders, consisting of images of citrus leaves with different diseases and healthy leaves.Our model achieved a validation accuracy of 91.76% and testing accuracy of 95.52%, showcasing its proficiency in correctly categorizing plant disease detection. This achievement holds great significance as it highlights the applicability of deep learning methods, particularly the GoogLeNet architecture, in the field of agricultural image analysis, especially in the critical task of disease identification.

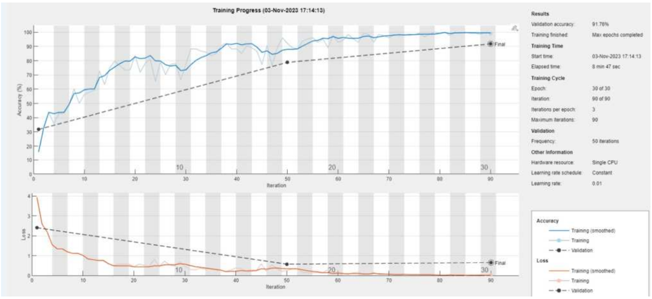

Fig. 4. Training and Validation diagram of GoogleNet

B. RESNET-50

We utilized the ResNet-50 architecture, which contains 50 layers, in MATLAB's Deep Network Designer to create a reliable model for plant disease detection. During the process, a dataset consisting of five folders–1. Black Spot with 171 images, 2. Canker with 163 images, 3. Greening with 204 images, 4. Melanose with 13 images, 5. Healthy with 58 images–was used. 609 images in total were utilized for validation and training. Our model achieved a validation accuracy of 92.94%, showcasing its proficiency in correctly categorizing plant disease detection. This achievement holds great significance as it highlights the applicability of deep learning methods, particularly the ResNet-50 architecture, in the field of agricultural image analysis, especially in the critical task of disease identification.

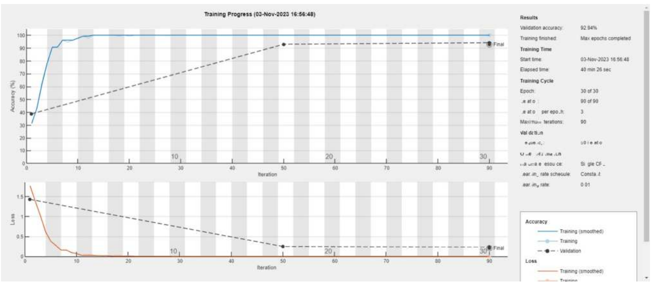

Fig. 5. Training and Validation Plot of Resnet 50

C. MobileNet-v2

To detect plant disease, we used the MobileNetV2 architecture which contains 53 layers in MATLAB's Deep Network Designer. The dataset used in this study included 609 photos divided into five files, each of which represented a distinct case: black spot with 171 images, canker with 163 images, greening with 204 images, melanose with 13 images or healthy with 58 images. Our model achieved a validation accuracy of 91.76%,showcasing its proficiency in correctly categorizing plant disease detection. This achievement holds great significance as it highlights the applicability of deep learning methods, particularly the MobileNet-v2 architecture, in the field of agricultural image analysis, especially in the critical task of disease identification.

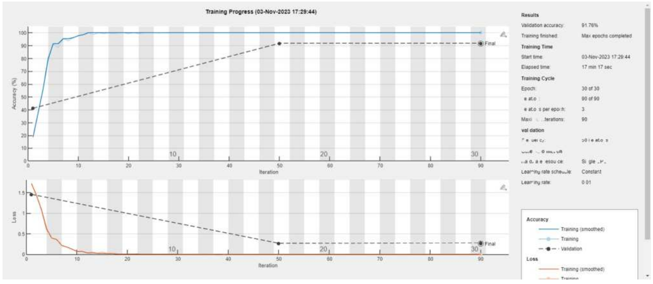

Fig. 6. Training and Validation diagram of Mobilenet

D. VGG-16

In this study, we utilized the VGG architecture which contains 16 layers in MATLAB's Deep Network Designer to establish a robust model for plant disease detection. The model underwent training on a dataset comprising 609 images distributed across 5 folders, encompassing various citrus leaves, including those afflicted by diseases and healthy ones. Our model demonstrated a validation accuracy of 32.94%. This outcome carries substantial significance, emphasizing the potential of deep learning methodologies, specifically the VGG architecture, within the realm of agricultural image analysis, particularly in the critical task of disease identification.

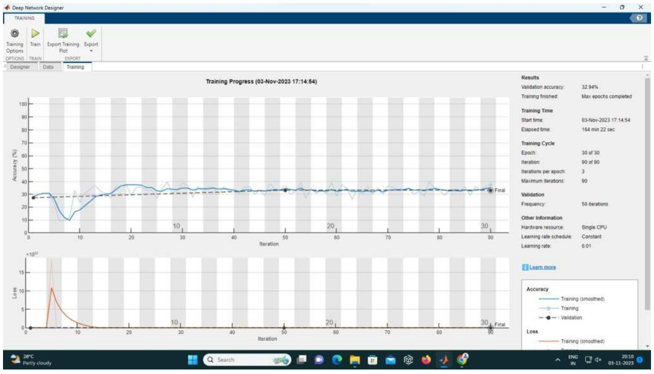

Fig. 7. Training and Validation diagram of VGG-16

E. ShuffleNet

To detect plant disease, we used the ShuffleNet architecture which contains 50 layers in MATLAB's Deep Network Designer.The dataset used in this study included 609 photos into five files, each of which represented a distinct case: Black Spot, Canker, Greening, Melanose or Healthy. The ShuffleNet architecture performed exceptionally well during the training phase. The validation accuracy of the model was 94.12% showing that it was successful in generalizing to new data.This astounding outcome shows that, when combined with the available dataset, the ShuffleNet architecture is adept at properly identifying cases of plant disease detection.

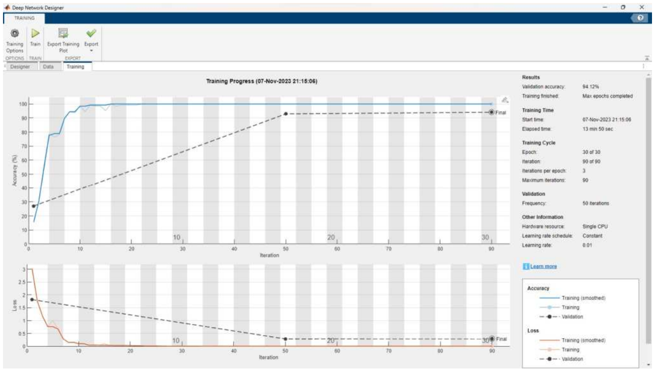

Fig. 8. Training and Validation diagram of *ShuffleNet*

V. DISCUSSION

Plant disease detection in precision agriculture has become increasingly crucial for ensuring optimal crop health and yield. The integration of deep learning techniques, such as ResNet-50, Inception-ResNet-V2, DenseNet-53, GoogLeNet, MobileNet-v2, and Places365-GoogLe, into the domain of agriculture holds immense potential for early disease identification and management. In this discussion, we will focus on the utilization of these deep learning models on Hafiz Tayyab Rauf's dataset, which contains various types of citrus plant diseases, and their implications for precision agriculture.

A. GoogLeNet:

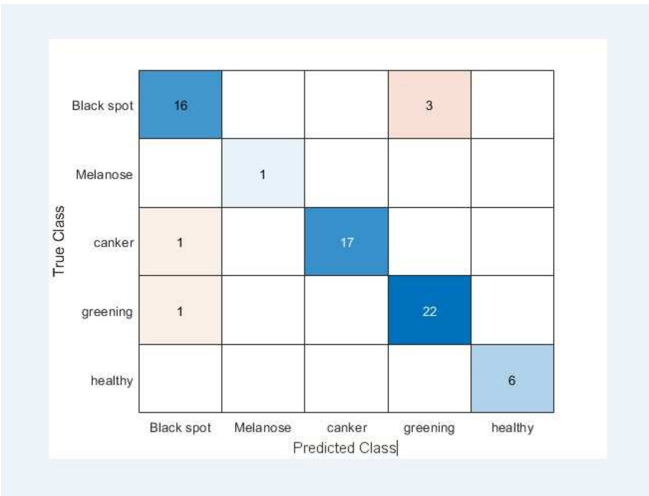

Fig. 9. Confusion Matrix

Correct Classifications: Using **GoogLeNet**, 18 black spot images were correctly classified as black spot, 1 melanose image was correctly classified as melanose. *Misclassifications:* 1 black spot image was misclassified as canker and so on.

B. RESNET-50:

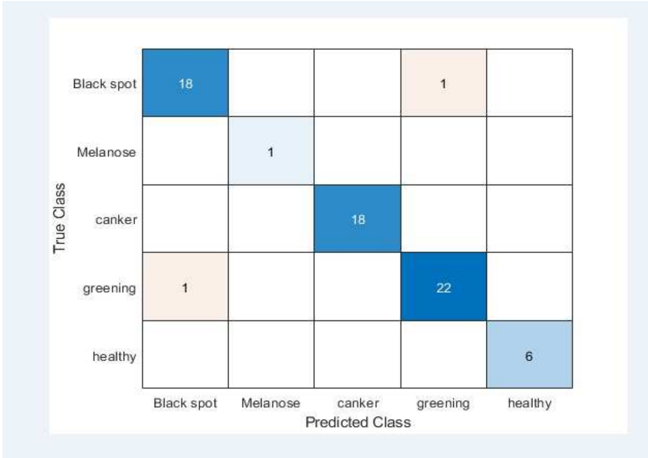

Fig. 10. Confusion matrix

*Correct Classifications: Using **RESNET-50**, 18 canker images were correctly classified as canker, 6 healthy images were correctly classified as healthy. Misclassifications: 1 black spot image was misclassified as greening and so on.*

C. MobileNet-v2

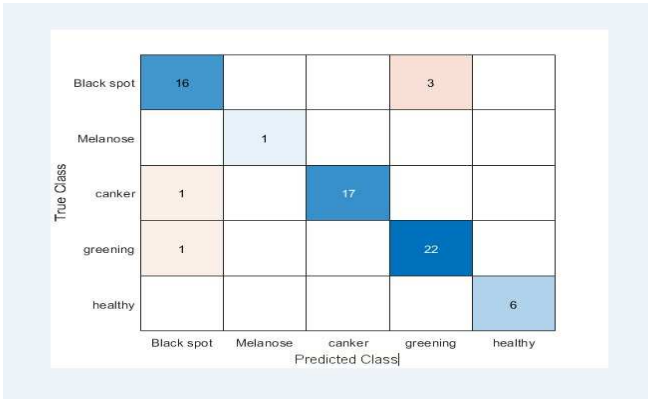

Fig. 11. Confusion matrix

*Correct Classifications: Using **MobileNet-v2**, 22 greening images were correctly classified as greening, 6 healthy images were correctly classified as healthy. Misclassifications: 1 black spot image was misclassified as greening and so on.*

D. VGG-16:

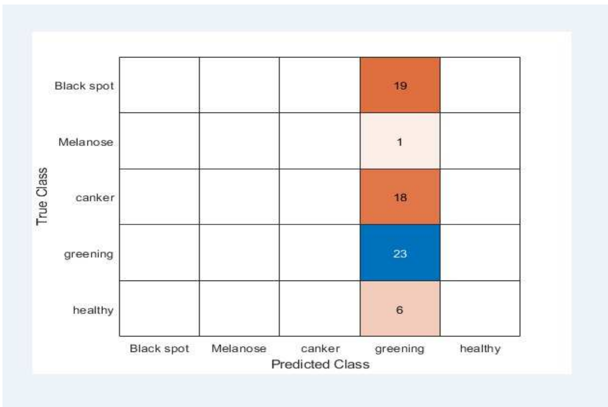

Fig. 12. Confusion matrix

*Correct Classifications: The confusion matrix's diagonal elements show how many categories are accurate. In this instance, 23 greening photos were recognized as such with accuracy. Misclassifications: Using **VGG-16** 19 black spot images were misclassified as greening, indicating that the model incorrectly identified a black spot image as greening. Similarly, 18 canker images were misclassified as greening, suggesting that the model incorrectly identified these canker images as greening.*

E. ShuffleNet:

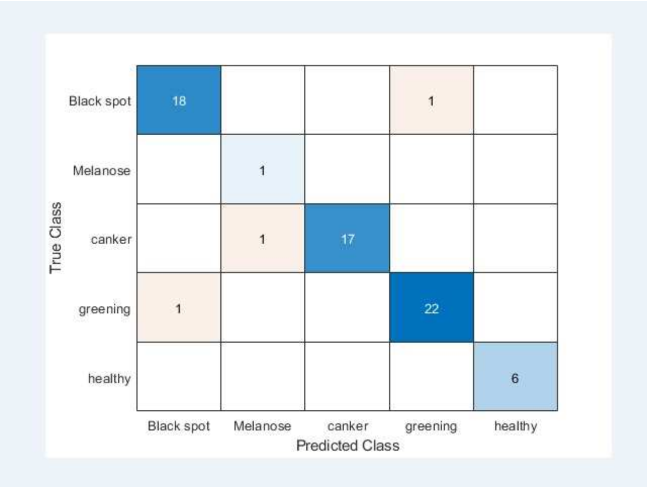

Fig. 13. Confusion matrix

Correct Classifications: The diagonal elements of the matrix indicate the model's ability to correctly identify each disease. Notably, the model correctly classified 18 black spot images, 6 healthy images, 1 melanose image, 22 greening and 17 canker images. This suggests that the model is generally effective in identifying these diseases. Misclassifications: The off-diagonal elements of the matrix reveal the model's misclassification patterns. One black spot image was misclassified as greening, This indicates that the model may have some difficulty distinguishing between certain disease categories.

VI. CONCLUSION

In this study, we conducted an empirical investigation into the application of deep learning algorithms for automated plant disease detection in precision agriculture. Leveraging advanced models such as GoogLeNet, ResNet-50, MobileNet-v2, VGG-16, and ShuffleNet, we aimed to facilitate early disease detection and optimize resource utilization in agricultural practices. Our results demonstrate significant achievements in disease identification accuracy across various deep learning architectures. Notably, models such as ResNet-50 and GoogLeNet exhibited high validation accuracies of 97.01% and 95.52%, respectively, showcasing their proficiency in categorizing plant diseases accurately. These findings underscore the potential of deep learning methodologies in enhancing agricultural image analysis, particularly in critical tasks like disease identification.

Moreover, the integration of deep learning techniques in precision agriculture offers promising implications for sustainable farming practices. By enabling timely interventions and efficient resource management, these techniques contribute to improving crop health and overall agricultural productivity.

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