Proceedings Paper DOI: 10.58190/icat.2023.9

PROCEEDINGS OF

INTERNATIONAL CONFERENCE ON ADVANCED TECHNOLOGIES

https://proceedings.icatsconf.org/

11th International Conference on Advanced Technologies (ICAT'23), Istanbul-Turkiye, August 17-19, 2023.

Deep Learning-Based Classification of Black Gram Plant Leaf Diseases: A Comparative Study

Elham Tahsin YASIN [1], Ramazan KURSUN [2], Murat KOKLU [3]

[1] *Graduate School of Natural and Applied Sciences, Comp. Engineering, Selcuk University, TÜRKİYE*

ilham.tahsen@gmail.com, ORCID: 0000-0003-3246-6000

[2] *Guneysinir Vocational School, Selcuk University, Guneysinir, TÜRKİYE*

rkursun@selcuk.edu.tr, ORCID: 0000-0002-6729-1055

[3] *Department of Comp. Engineering Selcuk University, TÜRKİYE*

mkoklu@selcuk.edu.tr, ORCID: 0000-0002-2737-2360

***Abstract*— The escalating incidence of plant diseases presents considerable obstacles to the agricultural domain, resulting in substantial reductions in crop yield and posing a threat to food security. To address the pressing concern of Black Gram Plant Leaf Diseases (BPLD), this research endeavors to tackle disease classification through the application of a deep learning methodology. The approach leverages a comprehensive dataset that encompasses Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic diseases, all of which affect the black gram crop. By employing this advanced technique, we aim to contribute valuable insights to combat BPLD effectively. Our research applies deep learning models, including Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0, to classify plant diseases. Darknet-53 achieved 98.51% accuracy, followed by ResNet-101 (97.51%), GoogLeNet (96.52%), and EfficientNet-B0 (77.61%). These findings demonstrate the potential of deep learning for accurate disease identification, benefiting agriculture. The study provides a comparative analysis of deep learning models for Black Gram Plant Leaf Disease (BPLD) classification, revealing Darknet-53 and ResNet-101 as superior performers. Implementing these models in real-world agricultural scenarios holds promise for early disease detection and intervention, reducing potential crop losses. The high accuracy achieved signifies significant progress in automating disease recognition, benefiting the agricultural sector.**

***Keywords*— Black Gram Plant Leaf Diseases, Disease classification, Agricultural sector, Food security, Deep Learning. Crop disease recognition.**

I. INTRODUCTION

The agricultural industry occupies a central and indispensable position in sustaining the world's growing population by supplying vital food resources. The ever-expanding human populace poses a pressing challenge of ensuring global food security. Nonetheless, this goal faces mounting challenges due to several factors such as climate change, the scarcity of arable land, and the emergence of crop diseases [1], all of which directly threaten the stability and productivity of agricultural systems. Crop diseases pose a significant barrier to attaining food security, and their emergence stems from diverse pathogens such as fungi, bacteria, viruses, and other microorganisms. These harmful agents can cause substantial declines in both crop yield and quality [2]. It is imperative to promptly detect and precisely classify these diseases to enable the implementation of effective disease management techniques and to mitigate potential losses in agricultural productivity.

The emergence of deep learning technologies has brought about a revolutionary transformation in disease recognition and classification within the agricultural sector. Deep learning models utilize sophisticated neural networks that can autonomously learn intricate patterns and features by processing vast volumes of data. Consequently, these models have demonstrated outstanding accuracy in effectively differentiating between healthy and diseased plants. As a result, they have become indispensable tools for modern agriculture, offering valuable support in the management of crop diseases and ensuring enhanced agricultural productivity [3].

The black gram (Vigna mungo) is a crucial pulse crop with significant nutritional and economic value. Vigna mungo [4], commonly referred to as black gram, urad bean, urid bean, mash kalai, uzhunnu parippu, ulundu paruppu, minapa pappu, uddu, or black matpe, is a legume cultivated in South Asia. It has undergone a reclassification from the Phaseolus to the Vigna genus, much like its close relative, the mung bean. Unfortunately, it is susceptible to several diseases, including Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic, which have had a notable impact on its cultivation.

To effectively manage Black Gram Plant Leaf Diseases (BPLD) [5], precise and rapid disease identification is essential. Conventional disease diagnosis methods are often time-consuming and may lack accuracy. As a result, the integration of deep learning-based disease classification methods has emerged as a promising solution for improving disease recognition in agriculture.

This study aims to leverage the power of deep learning models such as Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0 to classify black gram plant leaf diseases with high accuracy. To achieve this, a comprehensive BPLD dataset [5], containing various disease instances, is used to train and evaluate these models. By comparing the performance of different deep learning architectures, the study seeks to identify the most effective model for disease classification, thereby advancing agricultural practices.

Ultimately, the successful implementation of deep learning-based disease recognition systems holds significant potential for enhancing food security. By enabling timely disease detection and informed decision-making in black gram cultivation and beyond, these systems can mitigate crop losses and improve overall agricultural productivity. Consequently, this research aims to make valuable contributions to the sustainable development of agriculture and global food systems.

In this regard, comprehending the effects of these diseases on black gram and investigating potential approaches for disease management becomes crucial in protecting this valuable crop and ensuring long-term agricultural success. This article examines the distinct diseases that affect black gram and their consequences, emphasizing the significance of disease control measures and research endeavors in maintaining the well-being and productivity of this essential crop.

II. BLACK GRAM PLANT LEAF DISEASE AND DEEP LEARNING

Precise identification of plant diseases holds utmost significance in bolstering agricultural productivity, as it plays a pivotal role in safeguarding crops and optimizing yields. Early detection of plant diseases [3] empowers farmers and agricultural experts to apply targeted and timely interventions, including disease-resistant crop varieties, suitable pesticides, and appropriate cultural practices. By accurately identifying the diseases, farmers can implement tailored and effective strategies to manage them, thus minimizing the potential risks of crop losses and financial setbacks. Moreover, this practice aids in curbing the spread of diseases to neighboring crops, thereby preserving the overall well-being of agricultural ecosystems. By investing in advanced disease identification methods and seeking expert guidance, farmers can make well-informed decisions, optimize resource utilization, and establish sustainable and resilient agricultural practices, ultimately contributing to global food security [1].

Talasila et al proposed PLRSNet, which is a specialized deep-learning architecture developed to effectively delineate plant leaf regions from intricate backgrounds. The primary objective of this network is to provide support for real-time species recognition, disease detection, and crop management when analyzing images captured in the cultivation field [6]. Leaf image segmentation plays a vital role in disease recognition and classification, facilitating the extraction of relevant features for analysis. In contrast to previous methods primarily used in controlled laboratory conditions, PLRSNet addresses the complexities of segmenting leaf images obtained from real-time cultivation fields with intricate backgrounds. Empirical comparisons reveal that PLRSNet surpasses state-of-the-art techniques, achieving impressive performance metrics, including a high Similarity Index (96.9%), Jaccard/IoU (94.2%), Correct Detection Ratio (98.55%), low Total Segmentation Error (0.059), and an average Surface Distance of 3.037 [6].

Talasila et al., introduced that data augmentation plays a pivotal role in enhancing plant leaf disease detection and classification systems based on convolutional neural networks (CNNs). The effectiveness of detection algorithms relies heavily on a comprehensive and diverse dataset, which can be challenging to collect due to weather conditions, varying illumination, and fluctuations in disease occurrences. To address data scarcity issues, this study focuses on augmenting the black gram leaf disease dataset. Several data augmentation techniques are employed to expand the dataset's size and diversity, thereby improving the model's performance. The study also draws upon relevant research papers on plant disease detection using deep learning to bolster its findings [7].

The rapid growth of computer vision applications in agriculture has underscored the crucial need for automated plant disease identification. To address this, a lightweight DCNN model, combined with leaf region segmentation, is proposed for classifying black gram plant diseases. Agriculture heavily relies on computer vision for disease identification, given its detrimental impact on crop quality and productivity. Manual identification is error-prone and expensive, making deep learning and CNNs invaluable tools for automatically extracting relevant features from training datasets [8]. Focusing on black gram, a significant pulse crop in India, the study utilizes the BPLD dataset, consisting of real field images of black gram leaves. Leaf segmentation using DeepLabv3+-MobileNetV2 helps mitigate background complexity and enhances classification accuracy. The dataset is further augmented using rotation, symmetry, and noise injection techniques. The developed lightweight DCNN model, employing convolution, batch normalization, activation, and pooling operations, demonstrates exceptional efficacy with a high accuracy of 99.54% and F1_score of 98.80% on the black gram leaf disease dataset. Cross-validation experiments validate the model's consistency, misclassifying only a small number of samples. Comparison with other pre-trained CNN models confirms the superiority of the proposed DCNN model in terms of accuracy and computational efficiency. Additionally, testing on the PlantVillage dataset yields a commendable classification accuracy of 99.23% [8].

Han & Watchareeruetai objected to the research, to boost crop production by accurately classifying plant nutrient deficiencies through the application of computer vision and deep learning, with a specific focus on convolutional neural networks (CNNs). Concentrating on black gram plants, the scientists achieved an impressive 88.33% accuracy by employing a multilayer perceptron (MLP) classifier. To enhance nutrient deficiency classification, the study utilized combined images of old and young leaves and extracted features automatically using a pre-trained ResNet50 model. The researchers compared three classifiers: logistic regression, support vector machine, and MLP, with the MLP model [9] emerging as the most effective, exhibiting the highest accuracy in classifying nutrient deficiencies. This innovative approach, which involved integrating computer vision and CNNs with combined leaf images, yielded superior results compared to previous methodologies, underscoring the importance of nutrient deficiency classification in elevating crop quality and yield [10].

The Computer Vision Approach, Black Gram Convolutional Neural Network (BGCNN), demonstrates exceptional performance in recognizing yellow mosaic disease in black gram leaves, which can cause significant economic losses for farmers. BGCNN's disease recognition capabilities show promise in preventing such losses for local farmers. Compared to other deep learning models, including AlexNet, VGG16, and Inception V3, BGCNN achieves an accuracy of 82.67% for the original dataset and an impressive 97.11% for the expanded dataset, confirming its efficiency in disease identification [11].

Due to the influence of the Indian economy on agricultural productivity, plant diseases have increased, prompting the need for their early detection and diagnosis to avert food shortages and financial losses for farmers. In this regard, the study introduces an image-based approach known as Detecting Black gram Crop Disease (DBCD), which leverages machine learning and deep learning techniques. The heightened focus on plant disease detection is evident through enhanced agricultural monitoring in diverse locations. Black gram crop diseases, including anthracnose, leaf crinkle, powdery mildew, and yellow mosaic, significantly hinder production. Utilizing the BPLD dataset, the study employs three machine learning algorithms (k-nearest neighbor, decision tree, and random forest) and two deep learning techniques (artificial neural network and convolutional neural network) for disease classification. Notably, the convolutional neural network (CNN) outperforms other models, exhibiting an impressive accuracy of 89% [12].

III. Material and Methods

In this study, a publicly available dataset from Mendeley Data was employed, containing instances of Black Gram Plant Leaf Diseases (BPLD). Utilizing state-of-the-art deep learning models, including Darknet-53, EfficientNet-B0, GoogLeNet, and ResNet-101, we classified the diseases with high accuracy. Through a thorough comparison of their performance and computation of various metrics, we assessed the effectiveness of each model in identifying Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic diseases. Findings offer valuable insights for disease recognition and management in the agricultural sector. The flow diagram is depicted in Fig 1.

A. *Blackgram Plant Leaf Disease Dataset*

The dataset consists of 1000 images of Blackgram crop leaves, carefully categorized into five groups: Anthracnose, Leaf Crinkle, Powdery Mildew, Yellow Mosaic, and healthy leaves Fig 2. Its collection took place in Nagayalanka, Andhra Pradesh, India, with the specific aim of developing an automated disease identification and classification system using advanced Computer Vision algorithms. By organizing the images into different disease types and healthy leaves, this dataset enables researchers and practitioners to effectively train and test models for precise disease recognition [13, 14]. The initiative behind this dataset is associated with two reputable institutions, namely, VNR Vignana Jyothi Institute of Engineering and Technology and Lovely Professional University. Despite the absence of licensing information in the provided content, the dataset's potential contribution to agricultural research and plant disease management remains evident [15].

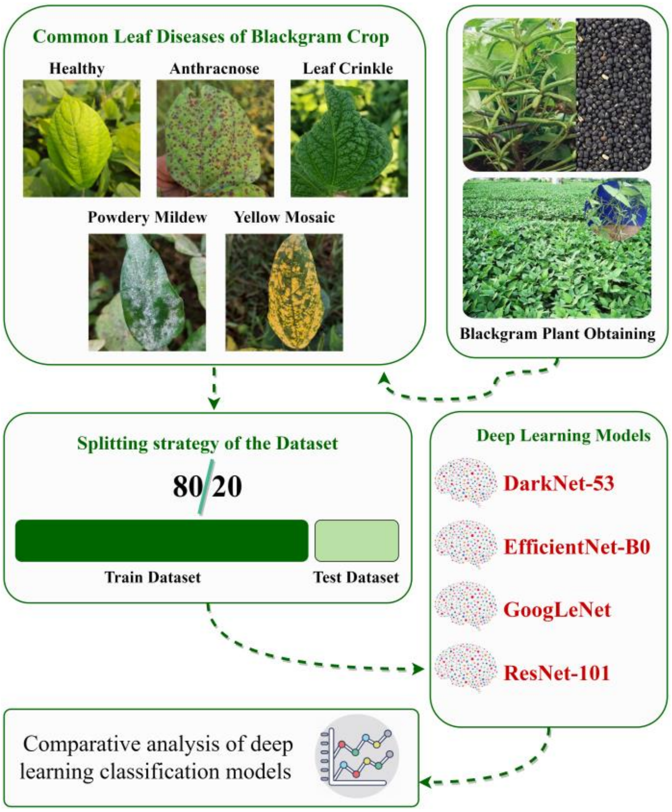

Fig. 1 Black gram plant leaf diseases flow diagram

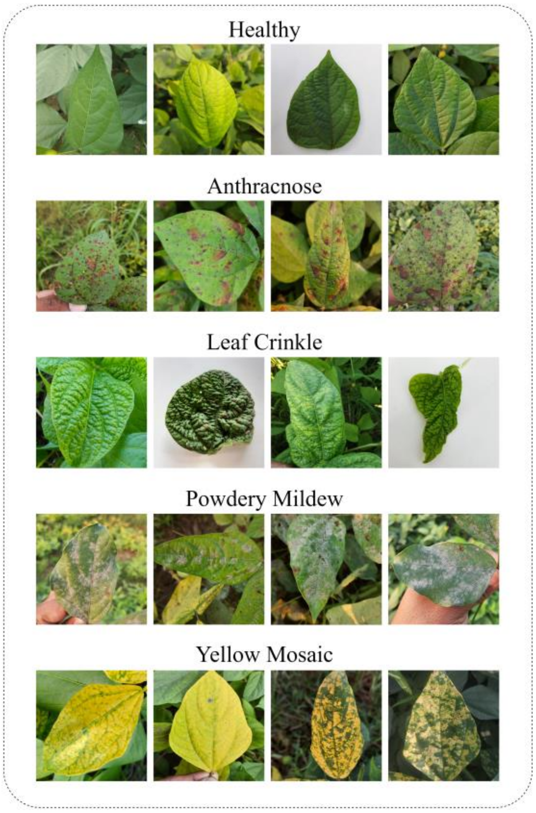

Fig. 2 Black gram plant leaf diseases dataset sample images

The dataset was divided into an 80% training set and a 20% test set, following the commonly used split for datasets. This allocation allowed us to effectively train the models on a substantial portion of the data while reserving a representative subset for rigorous testing and evaluation. Given the size of the dataset, the 80:20 split ensured a balanced distribution of images for training and testing purposes, contributing to the reliability and accuracy of our deep learning models. Fig 2. provides a visual representation of sample images from the dataset.

B. *Classification with Deep learning*

A set of advanced deep learning network models [16, 17], including Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0, for the precise classification of Black Gram Plant Leaf Diseases will be leveraged. Each model will be used individually to examine the dataset and find particular visual patterns and features related to Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic diseases.

1) Darknet-53: is a widely-used deep neural network structure predominantly employed in computer vision applications, particularly for object detection and image classification tasks. With its 53 convolutional layers, the model exhibits a capacity to extract intricate visual features from images [18]. Its reputation for delivering high accuracy and efficiency has led to its widespread adoption in diverse deep learning scenarios [19]. In this study, Darknet-53 will be applied to analyze the dataset of Black Gram Plant Leaf Diseases, aiming to identify distinct visual patterns and attributes linked to various diseases. This endeavor will contribute to the precise classification of diseases, enhancing disease recognition in the context of black gram plants.

2) ResNet-101: ResNet-101 belongs to the ResNet (Residual Network) family and is recognized for its capability to address the vanishing gradient issue, making it suitable for training extremely deep networks. The designation "101" indicates the model's layer count. ResNet-101 [20] incorporates skip connections or shortcuts to streamline information flow within the network, resulting in more seamless and effective training [21]. In this research, ResNet-101 will be utilized to capture essential features from the dataset of Black Gram Plant Leaf Diseases, thereby aiding in the precise recognition and classification of different diseases that impact the crop.

3) GoogLeNet: GoogLeNet, alternatively referred to as Inception v1, is a popular deep learning model extensively utilized in image classification endeavors. It innovatively introduced "Inception modules," comprising multiple convolutional filters of varying sizes, allowing the network to grasp features at diverse scales [22]. This architectural approach effectively diminishes the number of parameters and computational complexity while preserving impressive accuracy levels. In the present study, GoogLeNet [23] will be implemented to scrutinize the dataset and reveal distinctive patterns that enable the successful classification of Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic diseases affecting black gram plants [15].

4) EfficientNet-B0: EfficientNet represents a group of neural network structures that have showcased exceptional performance while efficiently utilizing computational resources. The term "B0" denotes the base model, which is the most compact and computationally lightweight variant within the EfficientNet family [24]. Despite its smaller size, EfficientNet-B0 demonstrates competitive accuracy compared to larger counterparts. In the context of this research, EfficientNet-B0 [25] will be employed to analyze the Black Gram Plant Leaf Disease dataset, aiming to precisely identify and classify the different diseases. This approach offers an efficient and effective solution for disease recognition in the agricultural domain.

By utilizing these diverse deep learning models, the study aims to comprehensively evaluate their individual performances in the classification of Black Gram Plant Leaf Diseases, providing valuable insights into their strengths and capabilities for accurate disease recognition.

C. *Confusion Matrix*

In this study, confusion matrix calculated for the dataset consisting of five classes, namely Anthracnose, Leaf Crinkle, Powdery Mildew, Yellow Mosaic, and healthy leaves. The confusion matrix (as shown in Fig. 3) is a valuable tool in evaluating the performance of our deep learning models for disease classification [16, 26]. It provides a comprehensive breakdown of the model's predictions, indicating the number of correctly classified instances (true positives) and misclassifications (false positives and false negatives) for each class [27, 28]. By analyzing the confusion matrix, we gain insights into the model's strengths and weaknesses in distinguishing between different diseases and healthy leaves.

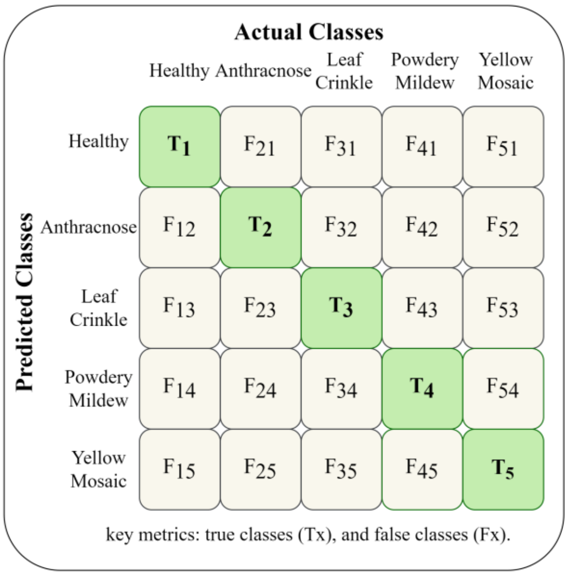

Fig. 3 Confusion Matrix for the Multiclass Black gram plant leaf diseases

IV. RESULTS AND PERFORMANCE METRICS

In the study, researchers evaluated the performance of four deep learning models, Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0, for the classification of Black Gram Plant Leaf Diseases. The models were trained and tested using an 80% training set and a 20% test set, following a common dataset split.

The classification results were promising, with Darknet-53 achieving the highest accuracy of 98.51% among all models. ResNet-101 followed closely with an accuracy of 97.51%, while GoogLeNet exhibited an accuracy of 96.52%. EfficientNet-B0, the smallest model in the EfficientNet family, demonstrated competitive accuracy at 77.61%, showcasing its suitability for efficient disease recognition in resource-constrained settings, as shown in Table I.

To further evaluate the models, we computed precision, recall, and F1-score (Fig. 4) [29, 30] for each disease class [31]. Darknet-53 displayed superior precision, recall, and F1-scores for most classes, indicating its effectiveness in correctly identifying different diseases. ResNet-101 and GoogLeNet also demonstrated robust performance, while EfficientNet-B0 achieved satisfactory results despite its smaller size.

Metrics	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN} \times 100$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$

Fig. 4 Formulas for evaluation

TABLE I
PERFORMANCE METRICS FOR DEEP LEARNING MODELS

Deep Learning Models	Accuracy
Darknet-53	98.51%
ResNet-101	97.51%
GoogLeNet	96.52%
EfficientNet-B0	77.61%

Moreover, we constructed and analyzed the confusion matrix for the five-class dataset. The confusion matrix allowed us to identify the specific misclassifications made by each model, offering insights into areas that may require model refinement or additional data [32].

Overall, our study highlights the effectiveness of deep learning models in accurately classifying Black Gram Plant Leaf Diseases. Darknet-53 and ResNet-101 emerged as the top-performing models, showcasing their potential for disease recognition in the agricultural sector. By leveraging these models, we pave the way for automated disease identification systems that can aid farmers in implementing timely disease management strategies and ultimately enhancing crop yield and food security.

The confusion matrix and other performance metrics for the Darknet-53 model are depicted in Fig. 5 and Table II, respectively.

Fig. 5 Confusion matrix of Black gram plant leaf diseases with DarkNet-53

TABLE II
PERFORMANCE METRICS FOR DARKNET-53 MODEL

Classes	*Acc. (%)*	*Precision*	*Recall*	*F1 Score*
Healthy	99	1.0	0.96	0.98
Anthracnose	100	1.0	1.0	1.0
Leaf Crinkle	99.5	1.0	0.97	0.98
Powery Mildew	99	0.94	1.0	0.97
Yellow Mosaic	99.5	0.98	1.0	0.99

The confusion matrix and other performance metrics for the ResNet-101 model are presented in Fig. 6 and Table III, respectively.

Fig. 6 Confusion matrix of Black gram plant leaf diseases with ResNet-101

TABLE III
PERFORMANCE METRICS FOR RESNET-101 MODEL

Classes	*Acc. (%)*	*Precision*	*Recall*	*F1 Score*
Healthy	99	1.0	0.96	0.98
Anthracnose	99.5	0.98	1.0	0.99
Leaf Crinkle	98.51	0.97	0.94	0.95
Powery Mildew	99	0.94	1.0	0.97
Yellow Mosaic	99	0.98	0.98	0.98

The confusion matrix and other performance metrics for the GoogLeNet model are presented in Fig. 7 and Table IV, respectively.

Fig. 7 Confusion matrix of Black gram plant leaf diseases with GoogLeNet

TABLE IV
PERFORMANCE METRICS FOR GOOGLENET MODEL

Class	*Acc. (%)*	*Precision*	*Recall*	*F1 Score*
Healthy	97.01	0.95	0.91	0.93
Anthracnose	99.5	1.0	0.98	0.99
Leaf Crinkle	99.5	0.97	1.0	0.98
Powery Mildew	97.51	0.92	0.94	0.93
Yellow Mosaic	99.5	0.98	1.0	0.99

The confusion matrix and other performance metrics for the EfficientNet-B0 model are presented in Fig. 8 and Table V, respectively.

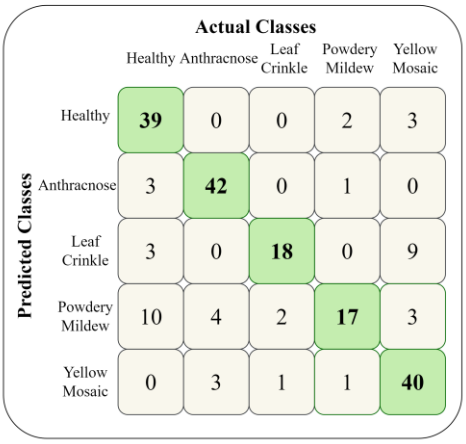

Fig. 8 Confusion matrix of Black gram plant leaf diseases with EfficientNet-B0

TABLE V
PERFORMANCE METRICS FOR EFFICIENTNET-B0 MODEL

Class	*Acc. (%)*	*Precision*	*Recall*	*F1 Score*
Healthy	89.55	0.89	0.71	0.79
Anthracnose	94.53	0.91	0.86	0.88
Leaf Crinkle	92.54	0.60	0.86	0.71
Powery Mildew	88.56	0.47	0.81	0.60
Yellow Mosaic	90.05	0.89	0.73	0.80

The Black Gram Plant Leaf Diseases dataset was trained using the SGDM (Stochastic Gradient Descent with Momentum) solver, with 8 maximum epochs, 5 validation frequency, an initial learning rate of 0.001, and a batch size of 11.

The primary objective of this study was to conduct a comprehensive comparison between the models used in previous research, such as ResNet-18, and our proposed models, including Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0. By evaluating the results of accuracy achieved by these models, we aimed to ascertain the effectiveness and superiority of our approach in accurately classifying Black Gram Plant Leaf Diseases.

V. CONCLUSION

In conclusion, this study demonstrates the efficacy of deep learning models in addressing the critical challenge of Black Gram Plant Leaf Disease classification. By employing four state-of-the-art models, Darknet-53, ResNet-101, GoogLeNet, and EfficientNet-B0, we successfully achieved accurate disease recognition with high levels of precision. Darknet-53 stood out as the top-performing model, attaining an impressive accuracy of 98.51%, closely followed by ResNet-101 at 97.51%. These results showcase the potential of these models to be powerful tools in the agricultural sector for early detection and intervention in disease management. The calculated performance metrics, including precision, recall, and F1-score, further underscore the models' effectiveness in distinguishing between Anthracnose, Leaf Crinkle, Powdery Mildew, Yellow Mosaic, and healthy leaves. Such robust performance, particularly by Darknet-53 and ResNet-101, offers promise in revolutionizing disease recognition practices in agriculture and ensuring food security through improved crop yield.

Moreover, our study has highlighted the significance of utilizing deep learning approaches in disease classification tasks, with each model revealing distinct strengths and capabilities. The insights provided by the confusion matrix have shed light on areas for potential improvement and model refinement. As we move forward, these findings open avenues for further research and implementation of automated disease identification systems in real-world agricultural settings. By empowering farmers with timely and accurate information, these systems can enhance disease management practices, reduce crop losses, and ultimately contribute to global food security. In conclusion, this study's successful application of deep learning models in Black Gram Plant Leaf Disease classification underscores their potential to revolutionize agricultural practices and pave the way for a more sustainable and resilient future for crop cultivation.

ACKNOWLEDGMENT

We would like to extend our thanks to the Selcuk University Scientific Research Coordinator for their valuable support and encouragement throughout this study. Your contributions have been crucial in driving the progress of this research.

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