Deep Learning-Based Cucumber Leaf Classification Using MobileNetV2: *A comprehensive analysis through K-Fold Cross-Validation*

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Abstract-- Cucumbers, a vital global crop, face significant challenges from diseases that can impact production and quality. This study introduces an automated model utilizing the MobileNetV2 architecture for deep learning-based leaf classification in cucumbers. The experiment evaluates the model's effectiveness through a comprehensive analysis, including a confusion matrix, K-fold cross-validation, and visualization of training and validation losses. Results demonstrate high accuracy in distinguishing healthy and diseased cucumber leaves, with an overall average accuracy of 96.81%. The study proposes a robust methodology and compares different architectures, contributing to the understanding of disease classification in plants. Future work will extend the scope to include diverse bacterial, viral, fungal, and viral-related disease databases. This research offers valuable insights into disease management in cucumber crops, contributing to sustainable and profitable farming practices.

Keywords- Deep Learning, Mobilenet-V2, Cucumber Leaf, Leaf Disease Classifications.

I. Introduction

Cucumbers, as a pivotal crop with global consumption, confront significant challenges posed by diseases that have the potential to adversely affect their production, impacting both the quality and quantity of yields. The significance of cucumbers in meeting global demand, especially with around 30% of production originating from small farmers in Latin America and Africa, highlights the necessity for effective disease management strategies [1]. Diseases like angular leaf spot and cucumber rust present considerable threats, leading to the utilization of pesticides and other control measures. However, the widespread use of these measures raises concerns regarding human health and environmental impacts.

The early detection of diseases is essential for safeguarding cucumber crops against these threats. The benefits of early detection are multifaceted, encompassing the reduction of losses, preservation of crop quality, and enhancement of overall farm profitability [2]. With the progression of machine learning and intensive learning approaches, the automatic identification of crop diseases has become viable. This report concentrates explicitly on applying the MobileNetV2 architecture for deep learning-based leaf classification in cucumbers. The thorough analysis includes exploring K-Fold cross-validation to assess the model's effectiveness in precisely classifying cucumber leaf diseases. As we delve into the details of this study, we will scrutinize the global demand for cucumbers, the challenges posed by diseases, and the crucial role that early disease detection, facilitated by deep learning approaches, plays in ensuring sustainable and profitable cucumber farming practices. The insights derived from this analysis have the potential to guide and refine disease management strategies, thereby contributing to the resilience and prosperity of cucumber cultivation on a global scale.

In this research, we use a customized model with the MobileNetV2 architecture to classify leaves. Our model, built on the efficient MobileNetV2 framework, successfully classifies leaf images, as confirmed by k-fold cross-validation results. Visualizations further reveal consistent and stable patterns during the training process.

II. Literature Review

The automatic classification of diseases through images has drawn significant attention from researchers in recent years. Despite the improvements, these diseases remain a serious barrier to sustainable agriculture. Additionally, there is still an enormous demand for a serious procedure by a large team of specialists to periodically monitor these diseases at an early stage. This is because most of the existing disease classification and detection approaches rely solely on visual observation by experts for detecting plant diseases. However, deep learning models using different methods have effectively classified diseases in recent years.

Numerous experiments have applied deep learning-based models to classify and detect diseases in plant leaves across various crop species. Such as-
[3] Zhang et al. (2019) developed a convolutional neural network (CNN) to accurately identify cherry leaf disease caused by Podosphaera pannosa. The study implemented pre-trained GoogLeNet on the ImageNet dataset, applying transfer learning to increase CNN performance. The results examined CNN's precision with a testing accuracy of 99.6%. However, the dataset's usage of cell phone photographs caused worries about their quality compared to professional cameras, potentially impacting their real-world applicability. The study suggested the necessity for further exploration of misclassification examples to develop and improve the proposed strategy.

[4] Howlader et al. (2019) developed a deep convolutional neural network (D-CNN) for autonomous guava leaf disease diagnosis, achieving outstanding precision on the BUGL2018 dataset. The 11-layer D-CNN, based on AlexNet, shows strong performance with 98.74% training and 99.43% testing accuracy utilizing stochastic gradient descent. Comparative analyses with a linear SVM and other feature descriptors demonstrated the efficiency of the D-CNN approach. The study acknowledged dataset limitations and was designed to extend for broader leaf sickness evaluation.

[6] Militante et al. (2019) applied deep learning to recognize sugarcane diseases with 95% accuracy. The CNN model discovered seven categories, including several leaf diseases, while noting cost constraints with specialist equipment. The architecture uses convolution and pooling layers with ReLU activation and the Adam optimizer, attaining 95% accuracy after 60 epochs. Though successful, the study encouraged future testing with alternative models and settings.

[10] Aggarwal et al. (2023) use pre-trained deep neural networks for rice leaf disease classification, attaining 94% accuracy using EfficientNetV2B3. The work includes image processing on a dataset of 551 pictures, addressing bacterial blight, brown spot, and blast diseases. Future applications include mobile device-based disease identification and expanding the concept to other crops.

[13] Zhang et al. (2021) offer a UAV-based hyperspectral approach for the winter wheat leaf area index (LAI) estimate, attaining 0.89 precision with Xgboost. The study stresses LAI's usefulness for crop monitoring but lacks comparisons with existing methods and covers only three machine-learning algorithms. The research reveals a good correlation (>0.99) between UAV and ASD hyperspectral data during the 2018 wheat growth phases.

[14] Wu et al. (2020) propose a system using deep CNNs, including VGGNet, GoogLeNet, ResNet, and MultiModel_VGR, for autonomous detection and severity assessment of pepper bacterial spot disease. Transfer learning increases performance, resulting in an impressive accuracy of 95.34% on the PlantVillage dataset. However, dependence on a single dataset may limit generalization to other diseases or crops due to potential feature differences.

[15] Mustak Un Nobi et al. (2023) introduce GLD-Det, a real-time guava leaf disease detection model based on a modified MobileNet architecture. The model, created by transfer learning, outperforms existing models on benchmark datasets, displaying high accuracy, precision, recall, and AUC scores. While effective, the work must dive into specific issues in model creation or potential downsides of employing transfer learning and MobileNet for guava leaf disease detection.

Table:01 Comparison of Previous Approaches

Year	Plant Name	Deep Learning Architecture	Performance	Reference
2023	Apple	Cycle-GAN, ResNet	Accuracy=97.78%	Chen, Y. et al. (2023)
2023	Grape	SVM	Accuracy=83%	Gawande, A. et al. (2023)
2023	Sugarcane	VGG-19	Accuracy=92%	Kumar, P.A. et al. (2023)
2023	Potato	EfficientNet	Accuracy=98.12%	Nazir, T. et al. (2023)
2023	Grape	Densenet201	Accuracy=98.02%	Ahmhed, H. et al. (2023)
2022	Maize	Custom DL (MaizeNet)	Accuracy=98.5%	Kundu, N. et al. (2022)
2022	Tomato	GoogleNet	Accuracy=87.27%	Tarek, H. et al. (2022)
2022	Cucumber	Cubic SVM	Accuracy=93.8%	Khan, M.A. et al. (2022)
2022	Jute	YOLO-V7	Accuracy=99.5%	Nayar, P. et al. (20220
2022	Potato	Inception V4	Accuracy=97.59%	Andrew, J. et al. (2022)
2021	Grape	ResNet-50	Accuracy=97%	Kirti et al. (2021)
2021	Strawberry	VGG-16	Accuracy=94%	Abbas, I. et al. (2021)
2021	Sugarcane	CNN	Accuracy=94.58%	KP, A. and Anitha, J. (2021)
2021	Tomato	KNN	Accuracy=82.1%	Tan, L. et al. (2021)
2021	Grape and Mang	CNN	Accuracy=89%	Rao, U.S. et al. (2021)
2021	Apple and Grape	Yolo-V5	Accuracy=93.8%	Polder, G. et al. (2021)

In this study, we explore using a customized model that incorporates the MobileNetV2 architecture for classifying leaves. Our model includes a MobileNetV2 framework as its foundation, followed by a classifier. We chose MobileNetV2 because it is known for its efficiency, making it well-suited for tasks with limited resources. The results from k-fold cross-validation demonstrate that our model is effective in accurately classifying leaf images. The visualizations associated with these results show consistent and stable patterns during the training process.

III. Methodology

A. Data Acquisition

The dataset utilized in this study comprises images sourced from the Kaggle online repository, explicitly focusing on cucumber leaf diseases. The dataset encompasses 596 images categorized into "ill cucumber" and "good cucumber." From this dataset, 500 images were selected for training and testing. Specifically, 181 images were designated for training, while 94 were set aside for testing and validation.

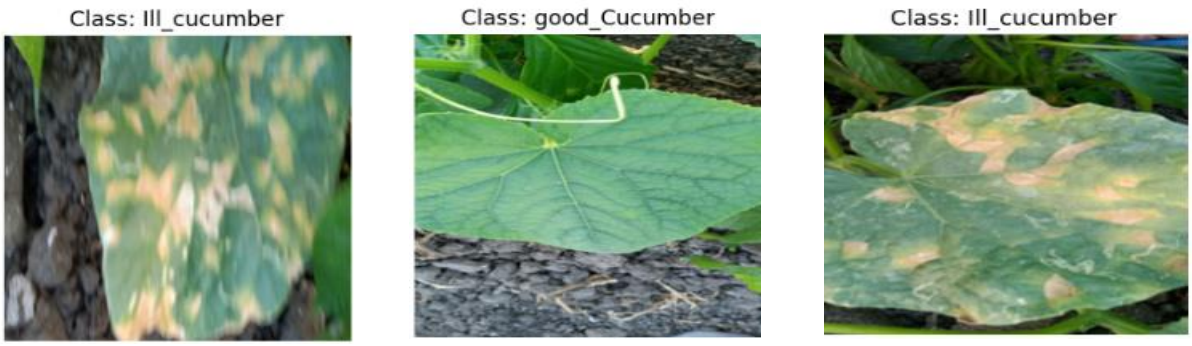


Fig:01 Dataset Sample

B. Image Pre-processing

The primary objective of image preprocessing is to enhance image quality and prepare it for subsequent processing by eliminating unwanted parts from the background of leaf images. Employing filters was instrumental in mitigating noise and high-frequency components. The leaf image preprocessing process is described below:

a) Resize

Resize photos to a uniform (256 x 256-pixel) scale to standardize their dimensions. Maintaining uniformity in the dataset, fostering fast processing, and fostering consistency in the framework depend on this stage.

b) Normalization

Normalization must be followed to standardize pixel values throughout each channel (RGB). The principal aim is to improve training stability and convergence by scaling pixel values to a predetermined interval. This normalization process is essential to enabling reliable and effective model training. Combined, these processes improve the image's quality and suitability for further processing.

C. Feature Extraction

The MobileNetV2 Backbone is applied for hierarchical feature extraction, forming a standard convolutional layer and progressing through inverted residual blocks. This architecture incrementally augments feature map channels. Following feature extraction, Global Average Pooling (GAP) reduces spatial dimensions, ensuring a consistent fixed-size representation. This intelligent combination promotes successful feature extraction for our technique.

D. Model Architecture

The model architecture in the provided code is based on MobileNetV2, a streamlined convolutional neural network architecture tailored for efficient deployment on mobile and edge devices. MobileNetV2 is the backbone, leveraging depth-wise separable convolutions to reduce computational complexity while maintaining expressive power. The architecture is augmented with a custom classification head, consisting of a Global Average Pooling 2D layer and a Dense layer with SoftMax activation, enabling multi-class image classification. Combining MobileNetV2 and the custom head creates a compact yet practical model for recognizing image patterns and features. The model is compiled with the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric. During training, data augmentation using TensorFlow's ImageDataGenerator enhances model generalization by presenting diverse views of the input data. The resulting architecture is computationally efficient and adept at accurately classifying images into predefined categories, making it well-suited for applications with resource constraints.

E. Classification

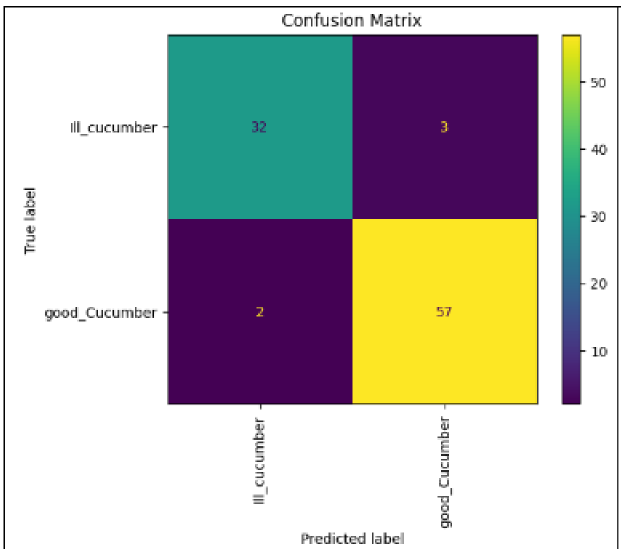
The classifier used in the provided code employs the MobileNetV2 architecture, a lightweight convolutional neural network specifically designed for mobile and edge devices. The MobileNetV2 model is the base, and a custom classification head is appended. The classification head includes a Global Average Pooling 2D layer to reduce spatial dimensions, followed by a Dense layer with a SoftMax activation function, facilitating multi-class classification. The model is compiled using the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric. Data augmentation is applied during training using TensorFlow's ImageDataGenerator to enhance model generalization. The training involves presenting batches of augmented data to the model, optimizing weights through backpropagation, and iteratively minimizing the loss function. The model's performance is evaluated on a test dataset to assess its accuracy in classifying images into predefined categories. This classifier leverages the efficiency of MobileNetV2 and is trained to recognize patterns and features for accurate image classification.

IV. Result and discussion

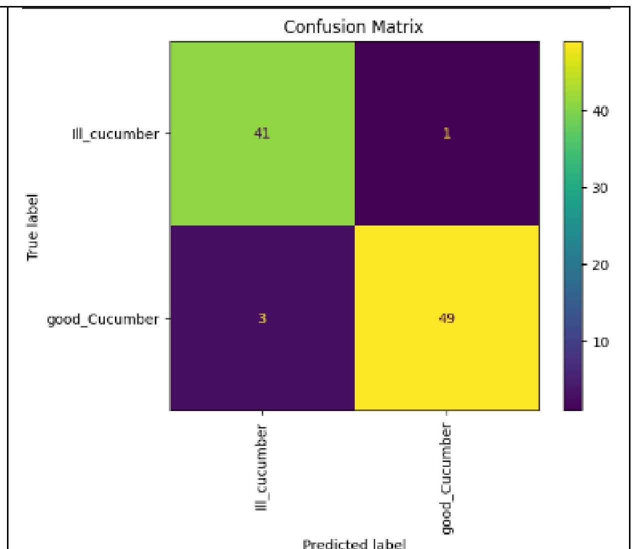
In this experiment, we utilize the MobileNet-V2 model within TensorFlow, implemented on the Python platform, for CPU-based processing. The dataset comprises two classes: "good cucumber" and "ill cucumber," with 242 and 227 examples, respectively. The dataset is partitioned into training (281), test (94), and validation (94) sets. The primary goal is to construct a resilient deep-learning model that precisely classifies cucumber leaves as healthy or diseased. This endeavor contributes to enhancing the accurate identification and management of cucumber diseases.

1. Confusion Matrix:

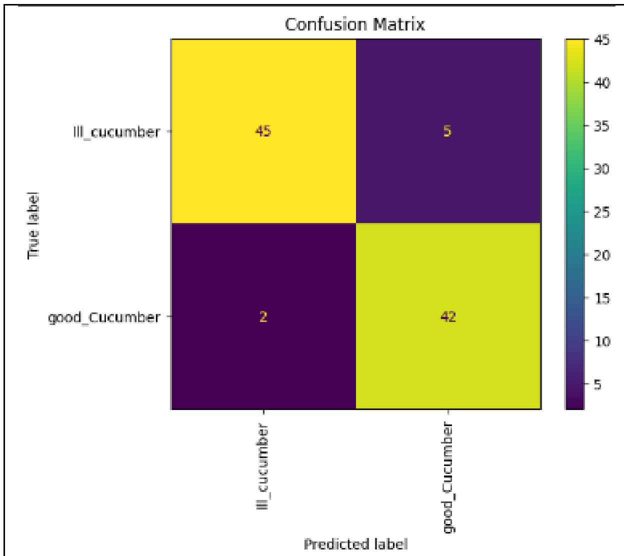
A confusion matrix is a fundamental tool for assessing the performance of a classification model. It provides a comprehensive breakdown of the model's predictions by categorizing them into four outcomes: true positives (correctly predicted positive instances), true negatives (correctly predicted negative instances), false positives (incorrectly predicted as positive), and false negatives (incorrectly predicted as unfavorable). These metrics are essential for evaluating the model's precision, accuracy, and other performance measures. By examining the confusion matrix, analysts can gain insights into the strengths and weaknesses of a model, especially in distinguishing between different classes.



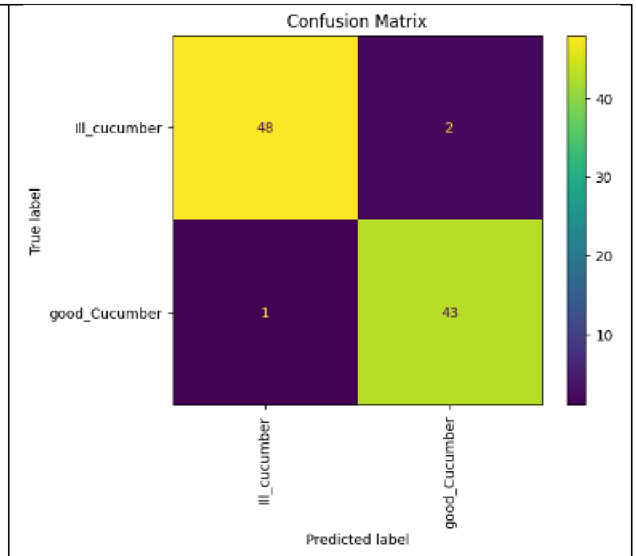
Fold-01



Fold-02



Fold-03



Fold-04

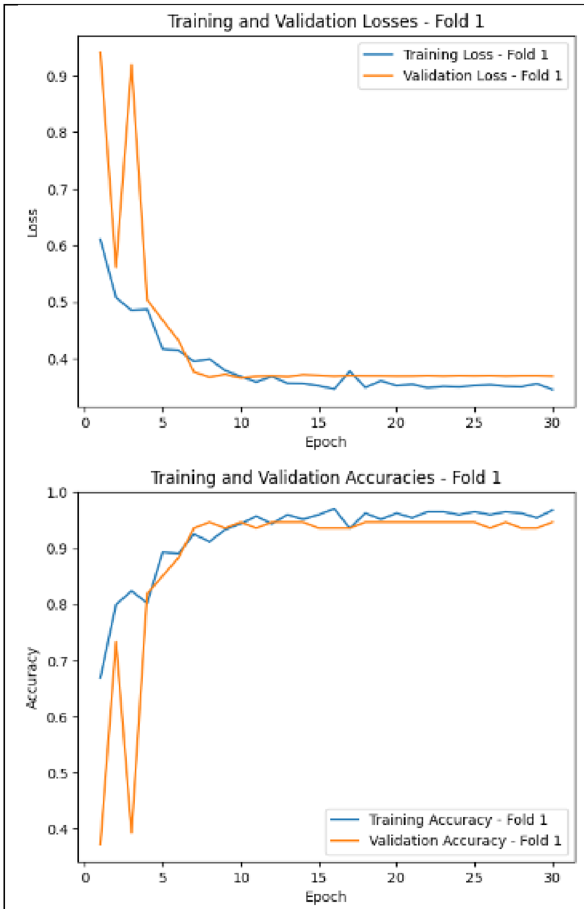
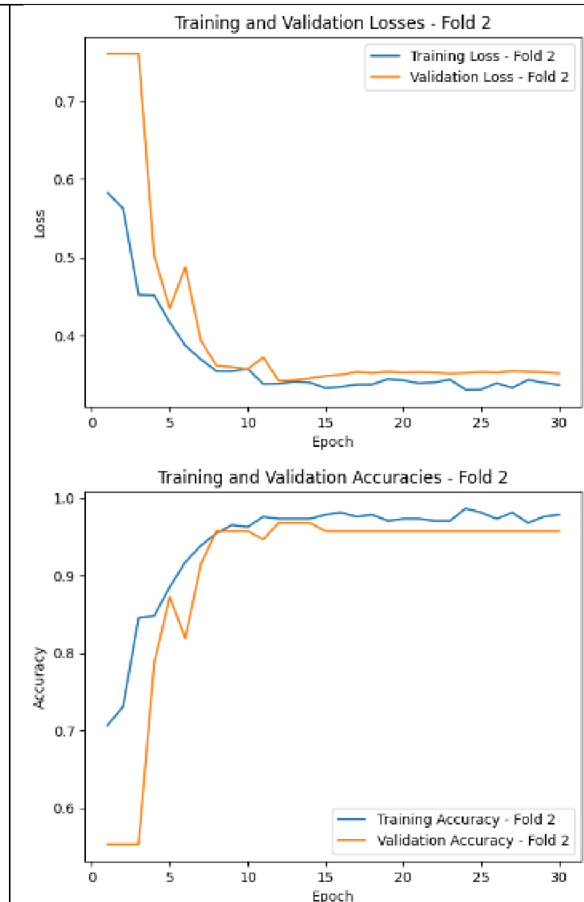
Fig:02 Confutation Metrix of different fold

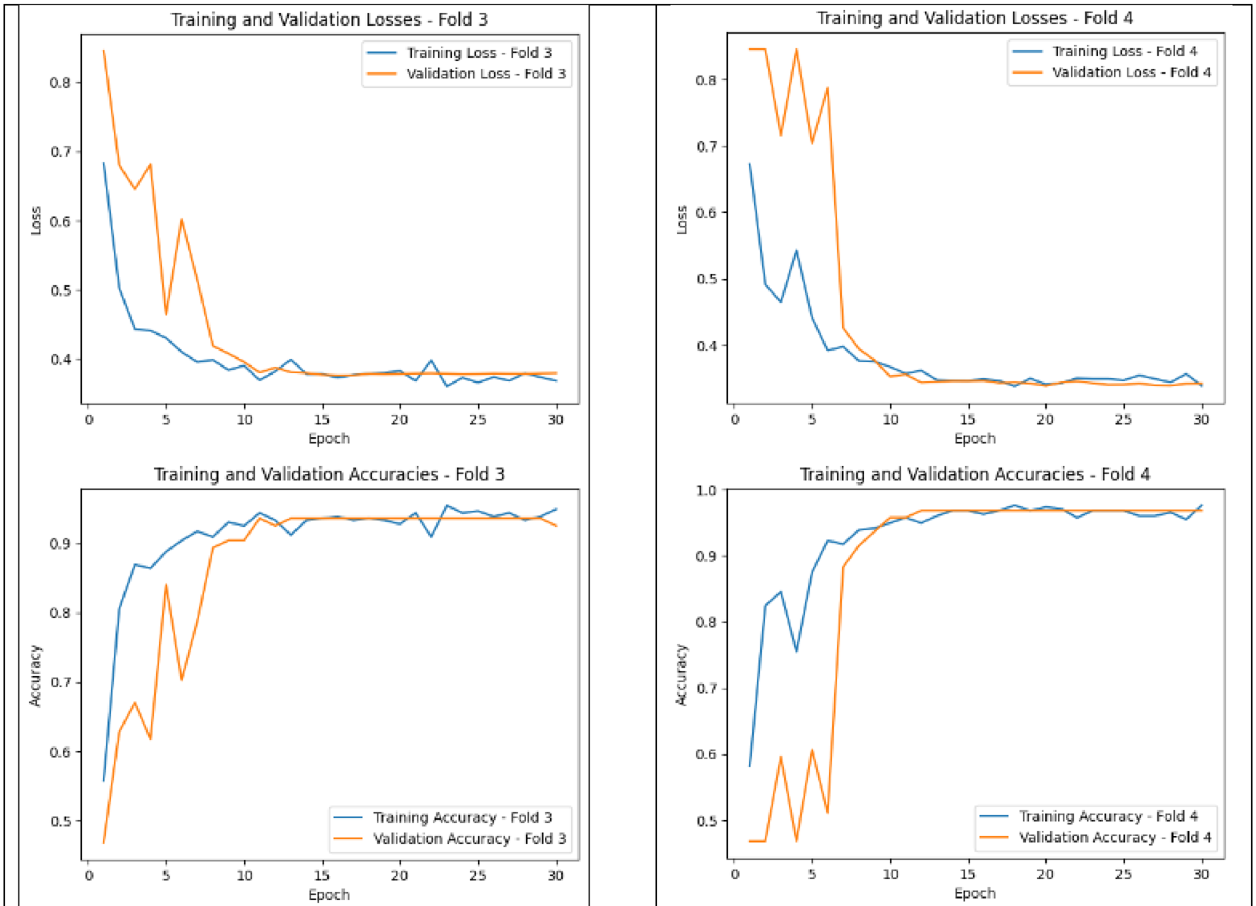
2. K-Fold Cross-Validation:

K-Fold Cross-Validation is a robust technique for estimating a model's performance across diverse datasets. The dataset is divided into K subsets, and the model is trained and validated K times, each time using a different fold for validation and the remaining folds for training. This approach helps mitigate the impact of dataset variability and ensures a more reliable evaluation of a model's generalization ability. The final performance metric is often an average across all K iterations, providing a more stable and representative assessment of the model's overall performance.

3. Training and Validation Loss:

During the training phase of a machine learning model, two crucial metrics are monitored: training loss and validation loss. Training loss measures the error in the training data and is used to optimize the model's parameters. Validation loss, on the other hand, evaluates the model's performance on a separate dataset not used during training, offering insights into its generalization capability. Both losses should decrease during training. A significant gap between training and validation losses may indicate overfitting, emphasizing the need for regularization techniques.

	
Fold- 01	Fold-02



Fold-03	Fold-04

Fig:03 Training and Validation losses of different folds

Training and Validation losses across different folds provide insights into the model's learning dynamics and generalization performance. The Folds 1 to 4 plotted graphs depict the training and validation losses over epochs. In an ideal scenario, both losses should decrease during training, indicating effective learning. However, disparities between training and validation losses can signify potential issues.

For Fold 1, the model consistently decreases training and validation losses, suggesting effective learning without overfitting. In Fold 2, although both losses decrease, a slight divergence between them appears, indicating a potential risk of overfitting. Fold three exhibits a scenario where the model's performance on the validation set plateaus while the training loss decreases, signaling a need for regularization. In Fold 4, a convergence of training and validation losses is observed, suggesting a well-generalized model.

These observations underscore the importance of monitoring and interpreting Training and Validation losses to optimize model performance. Addressing discrepancies and achieving a balance between the two contributes to a robust and generalizable deep learning model.

4. Accuracy, Precision, Recall, and F1 Score:

Accuracy, precision, recall, and F1 score are key metrics used to assess the performance of a classification model. Accuracy represents the ratio of correctly predicted instances to the total instances, providing a general overview of overall correctness. Precision focuses on the accuracy of optimistic predictions, recall (sensitivity) measures the model's ability to capture all relevant positive instances, and the F1 score combines precision and recall into a single metric. This combination offers a balanced evaluation that is particularly useful when dealing with imbalanced datasets. These metrics collectively guide decision-making processes for model selection, fine-tuning, and optimization for real-world applications.

Fold No	Class	Accuracy (%)	Recall (%)	F1-score (%)
1	Ill Cucumber	94	91	93
	Good Cucumber	95	97	96
2	Ill Cucumber	93	98	95
	Good Cucumber	98	94	96
3	Ill Cucumber	96	90	93
	Good Cucumber	89	95	92
4	Ill Cucumber	98	92	95
	Good Cucumber	91	98	94
5	Ill Cucumber	98	96	97
	Good Cucumber	96	98	97

Table:02 Performance evaluation of different folds

Accuracy (%)	Precision (%)	F1-score (%)	Recall (%)
96.81	94.67	94.66	94.68

Table:03 Average Performance Data

The performance evaluation of the MobileNet-V2 model on cucumber leaf classification reveals robust results across five folds of the dataset. For each fold, metrics such as Accuracy, Precision, F1-score, and Recall are presented for both "Ill Cucumber" and "Good Cucumber" classes. Notably, the model consistently demonstrates high accuracy, with an overall average of 96.81%. Precision values range from 90% to 98%, highlighting the model's ability to make accurate optimistic predictions. The F1-score, combining precision and recall, maintains a robust average of 94.66%, indicative of a balanced trade-off between precision and recall. Furthermore, recall values consistently exceed 90%, underscoring the model's effectiveness in capturing relevant positive instances. Collectively, these metrics showcase the model's reliability in distinguishing between healthy and diseased cucumber leaves, which is essential for practical applications in disease identification and crop management.

V. Conclusion And Future work

Cucumber leaves are susceptible to various diseases, leading to significant damage to cucumber crops and a decline in yield. Therefore, early detection and treatment of these diseases are crucial to enhance the quality and quantity of cucumber production. This research introduces an automated model, leveraging MobileNet-V2, images of cucumber leaves, and an efficient network architecture to classify and identify disease types accurately. The study proposes a methodology for categorizing cucumber leaf diseases and assesses and compares the efficacy of different architectures to identify the most suitable one for disease classification. The experimental results demonstrate the superior performance of the proposed method compared to other approaches in plant leaf disease classification. Optimal results are achieved when the model is trained with the Adam optimizer, a learning rate of 0.01, and a batch size of 32, which attains an accuracy of 96.81%.

Additionally, the study reveals an inverse relationship between batch size increase and learning rate decrease with classification training accuracy. These findings will inspire solutions for similar visual recognition challenges, extending the practical implications beyond cucumber leaf diseases. While the current focus is on cucumber leaf diseases, future work will enlarge the scope by including diverse databases encompassing bacteria, Viruses, fungi, and virus-related diseases.

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