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Deep Learning Based Classification of Guava Leaf Disease Using MobileNET

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Article

ABSTRACT

Plant disease detection is a key factor in improving the productivity of plants and crops while at the same time ensuring that there is a reduction in losses. The fruit of guava is classified as a tropical fruit and is extremely vulnerable to a number of diseases affecting the leaves. Therefore, there is a need to ensure that the diseases affecting the leaves of the guava fruit are identified in order to ensure proper control. This paper seeks to present a deep learning approach in the detection of diseases affecting the guava fruit using the MobileNetV2 approach. The approach ensures the efficient extraction of features while at the same time ensuring the applicability of the approach in smart agriculture. The approach was tested using the BU_Guava_Leaf Dataset and the Real Guava Fruit Diseases Dataset. The approach demonstrates the applicability of the approach in smart agriculture systems. All manuscripts must be accompanied by an abstract containing no more than 200 words. The abstract should briefly state the reason for the work, the significant results, and the conclusions. A graphical artwork representing the content of paper must be provided for manuscript.

Keywords: Plant Disease Detection(PDD), Image Classification, Deep learning(DL), MobileNetV2, Agricultural Automation, Convolutional Neural Networks(CNNs).

1. INTRODUCTION

Agriculture remains the backbone of most developing countries, providing employment, food, and contributing significantly to the country's GDP [1]. Despite this, plant diseases remain a threat to agricultural production, resulting in economic loss and reduction of quality of products [2]. Guava (Psidium guajava), a most common tropical fruit, is utilized for its nutritional and medicinal value and is highly susceptible to many diseases, including algal leaf spot, anthracnose, and whiteflies [3]. Disease diagnosis, in the conventional way, is mostly experience-based, which depends on the visual inspection of the diseased plant, a time-consuming and subjective process, and is mostly beyond reach in rural areas [4]. This has led to the development of smart and autonomous plant disease diagnosis systems that are capable of providing precise, rapid, and field-based diagnoses. Recent breakthroughs in deep learning, focusing on CNN, have revolutionized the field of image-based plant disease detection by providing the ability for automated feature extraction and identification [5]. Among the CNN models, it has been seen that lightweight CNN, i.e., MobileNetV2, is highly efficient in providing accuracy at a low computational cost, making it suitable for real-time applications in the field of agriculture [6]. MobileNetV2 combines depthwise separable convolutions and inverted residual connections with linear bottlenecks to achieve high performance on low-resource devices like mobile phones or embedded systems. Though research is on the rise, most prior research has used controlled or synthetic datasets like PlantVillage, which do not have the variability, lighting variation, and background noise of real-world agricultural settings. The limitations imposed by such confinement limit the applicability of models when they are implemented in real farming conditions. For filling this void, this paper makes use of two different datasets: the BU_Guava_Leaf (BUGL2018) dataset and the Guava Fruit Disease Dataset. The former consists of four classes of diseases gathered under controlled lab settings and the latter six disease classes recorded from natural agricultural fields with greater complexity and variability. The main aim of this study is to design and test a MobileNetV2-based deep model for classifying guava leaf diseases in structured and real-world settings.

Through the combination of the power of transfer learning and light architecture, this research hopes to overcome the disparity between laboratory-level precision and real-world field-level usability. Finally, this research lays out the place of deep learning in revolutionizing precision agriculture by offering scalable, affordable, and lightweight solutions to plant disease detection and management.

2. LITERATURE REVIEW

Deep learning technology has transformed the plant disease detection process with end-to-end models that don't require any feature extraction process. Traditional models, such as SVMs and decision trees, though basic models, suffered from poor generalization capabilities in actual-field scenarios, as they were based on feature extraction techniques [8]. CNNs resolved this problem through the

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extraction of spatial and texture features from images of leaves. Mohanty et al. [9] proved the robustness of CNNs with a staggering accuracy of 99.35% on the Plant Village dataset, which was taken with a uniform background. Accounting for the weakness of synthetic datasets, Barbedo [10] and Too et al. [11] highlighted real-world image variability and tested several CNN architectures with reported performances between 95% and 98%. Although deep models such as ResNet and Inception have high performance, they are computationally costly and not ideal for use on mobile devices. To rectify this, Howard et al. [12] and Sandler et al. [13] proposed MobileNet and MobileNetV2, respectively light CNN models that significantly save model size through the use of depth wise separable convolutions and inverted residual blocks. Sharma et al. [14] used MobileNet for real-time fruit disease detection with 99.30% accuracy on mobile phones, whereas Zhang et al. [15] added attention to MobileNetV2 and achieved 97.13% accuracy on challenging field images. Notwithstanding advances across crops such as tomato, potato, and maize, guava has had sparse attention. Saleem et al. [16] used ResNet-101 to train on a dataset acquired locally from guavas and obtained 97.74% accuracy, although the model was too large to deploy in real-time. Yadav et al. [17] used a custom CNN for field-acquired images of guavas and obtained 95.82% accuracy but did not investigate lightweight models. Our suggested study fills these voids by using MobileNetV2 on two datasets specific to guava: the lab-crafted BUGL2018 dataset and a real-world dataset of Guava Fruit Disease. Using this method enables the evaluation of performance on both laboratory and field settings while keeping the model lightweight enough for mobile and edge deployment.

Study	Dataset	Model	Real-World Data	Accuracy
Mohanty et al. [9]	Synthetic (PlantVillage)	Basic CNN	✕	99.35%
Barbedo [10]	Realistic Images	CNN / Segmentation	✓	~90%
Too et al. [11]	Mixed	ResNet, VGG, Inception	✓	95–98%
Howard et al. [12]	Benchmark	MobileNet	✓	94–96%
Sharma et al. [14]	Fruit Dataset (Real)	MobileNet	✓	96.47%
Saleem et al. [16]	Local Guava Dataset	ResNet, SqueezeNet	✓	97.74%
Yadav et al. [17]	Real Guava Leaves	CNN	✓	95.82%

Table 1: Comparison of Related Work

In spite of significant advances in the field of plant disease diagnosis, some key gaps remain in the current body of work. Most existing research, including that on the PlantVillage dataset, has been based on synthetic or highly controlled images that reflect neither realistic agricultural variability nor real-world imaging conditions. This leads to models that work well in laboratory settings but do not generalize when deployed under true field conditions. Moreover, not many research studies have examined guava-specific disease datasets, presenting a large gap in research studies targeting the economically valuable tropical fruit. Further, although high-performance models such as ResNet and Inception yield strong performance, their huge parameter size makes real-time deployment on mobile or edge devices accessed by farmers challenging. Therefore, there is an urgent requirement for a light, transferable, and effective deep learning model that can operate strongly on both structured and field-level guava datasets. The current research seeks to overcome these challenges through the implementation and validation of the MobileNetV2 architecture on varied guava disease datasets while ensuring scalability and field suitability.

3. MATERIAL AND METHOD

The preprocessing, augmentation, rigorous evaluation, and fusion-based decision-making have been applied to two guava datasets in the proposed model for improved classification accuracy. As shown in Fig. 1, the pipeline begins with dataset loading, followed by data splitting for training and testing. Preprocessing techniques were employed for resizing, normalization, and background noise reduction. Moreover, **Fig. 1** above also indicates the augmentation processes such as rotations and flipping, which are carried out before training. A MobileNetV2 model was used, along with fusion, to improve the performance on structured and real-world disease categories.

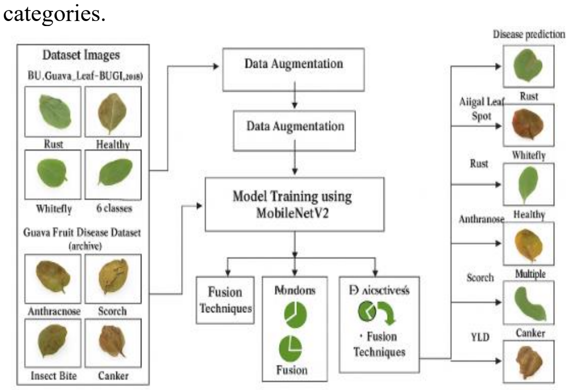

Figure 1. Workflow of the Proposed Guava Disease Detection Model

3.1 DATA STRUCTURE

The proposed model is validated and tested using two datasets specific to the Guava plant, namely the '**BU_Guava_Leaf-BUGL2018** dataset and the Guava Fruit Disease Dataset.' The **BUGL2018** dataset includes a number of high-resolution images of the leaves, captured under controlled conditions, and have four classes, namely Algal Leaf Spot, Rust, Whitefly, and Healthy. However, the archive dataset includes a number of large-scale images, captured in the field, and have six classes, namely Anthracnose, Canker, Mummification, YLD, Scorch, and Healthy. For the **BUGL2018 dataset**, the images were split into 2166 and 539 samples for the training and testing, respectively. For the archive dataset, a total of **540,000** images were used for the training, and **60,000** images were used for the testing. Augmentation techniques such as flipping, rotation, zoom, and brightness were used to enhance the generalization capabilities and handle the class imbalance problem. This hybrid dataset is used to validate the proposed model in a controlled environment and a natural environment, and the detailed description is shown in **Table 2.**

DataSet	Training	Testing	Augmented
BU_Guava_leaf(BUGL2018)	2166	539	850
Guava Fruit Disease(archive)	540,000	60,000	Applied

Table 2. Data Sample Count for Training, Testing, and Augmentation

Disease Name	Image	Symptoms	Cause
Whitefly		Leaf curling, yellowing, sticky residue (honeydew)	Infestation by *Bemisia tabaci* (whitefly insect pest)
Healthy Leaf		No discoloration or deformation; natural green color	Absence of pathogens and optimal environmental conditions
Algal leaf Spot		Circular, orange to reddish spots on upper leaf surface	Infection by *Cephaleuros virescens* (green alga)
anthracnose		Dark, sunken lesions; fruit and leaf rotting	Caused by *Colletotrichum gloeosporioides* fungus
Scorh		Leaf browning, drying from edges; sometimes with lesions	Fungal stress (*Macrophomina phaseolina*) or heat stress
Mix		Combination of multiple symptoms (spots, wilting, discoloration)	Multiple pathogens (fungi, bacteria, or pests)
Insect_bite		Visible holes, feeding marks, tissue damage on leaves	Chewing/sucking insects (e.g., beetles, caterpillars)
yld		Yellowing of veins and leaf lamina; stunted growth	Viral infection or nutrient deficiency

Table 3. Guava leaf disease and BU_Guava_Leaf - BUGL2018

Table 3 shows some common diseases found in the leaves of the guava plant, including the symptoms, causes, and control measures.

3.2 DATA PREPROCESSING

All the images have been resized to 224 × 224 pixels, which is the size needed by the MobileNetV2 architecture. Color images have been preserved in order to retain the texture and color features. Data augmentation enhances model generalization by applying rotation, horizontal and vertical flips, random cropping, and Gaussian noise, as illustrated in Fig. 2. These techniques simulate real-world image variability, improving robustness. Standard normalization is applied to rescale pixel values, ensuring consistent input distribution and accelerating model convergence.

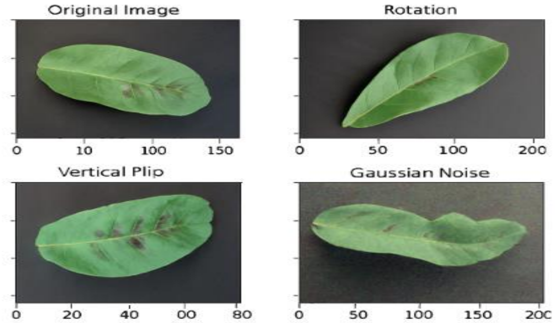

Figure 2. Dataset sample images after applying preprocessing & augmentation techniques

3.3 MOBILENETV2 - BASED CNN MODEL

In this research, MobileNetV2 was used as the base model for the classification of guava diseases because it is computationally efficient and achieves a high level of performance on mobile and embedded devices. MobileNetV2 enhances its previous version by adding depth wise separable convolutions, inverted residuals, and linear bottlenecks, which significantly decrease the number of parameters while ensuring accuracy.

As indicated in Fig. 3, the model pipeline starts with input images of 224×224×3, then followed by preprocessing and augmentation layers to increase variability. Feature extraction is achieved with MobileNetV2's stacked inverted residual blocks that conserve spatial and semantic information using less computation. The features are then passed through a global average pooling layer, followed by a fully connected dense layer with SoftMax activation that produces class probabilities for disease prediction.

Transfer learning was utilized by loading pre-trained weights on ImageNet, and fine-tuning it over both datasets of the current study. Categorical cross-entropy loss function was used and trained with Adam optimizer at a learning rate of 1×10^−4. Batch size and epochs were empirically optimized.

The final layer output y^i for class i is calculated using the SoftMax function:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where CCC is the total number of classe's (4 for BUGL2018, 6 for **.** Guava leaves disease). Accuracy is evaluated by comparing predicted outputs with true labels:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Prediction}$$

The overall flow the MobileNetV2 architecture, from input to output classifications, is illustrated in **Fig. 3**.

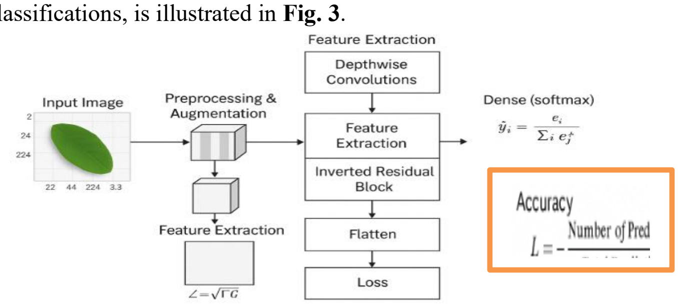

Figure 3. *MobileNetV2 Architecture Workflow for Guava Disease Detection*

3.4 EVALUATION OR TRAINING STRATEGY

For guaranteeing the proper training of the suggested MobileNetV2 model, a transfer learning strategy was employed by utilizing pretrained ImageNet weights. The model was fine-tuned on guava-specific datasets by replacing the top classification layer with a new dense layer based on the number of output classes—four for the BU_Guava_Leaf-BUGL2018 dataset and six for the Guava Fruit Disease Dataset. The data were split into training and test subsets with an 80:20 ratio. To ensure training stability and quicker convergence, input images were resized to 224×224 pixels and normalized by standard scaling. Data augmentation processes including horizontal and vertical flipping, random rotation, cropping, and Gaussian noise were performed in real time with Keras' Image Data Generator to enhance generalization and avoid overfitting. The model was trained with the Adam optimizer and learning rate of 1×10^−4, categorical cross-entropy loss, and batch size of 32. Both early stopping and learning rate reduction callbacks were employed to stop training upon convergence as well as fine-tune the learning rate during plateaus. Training was done for 10 epochs in both datasets.

3.5 Performance Evaluation Metrics

Performance metrics for evaluation are needed to judge the efficiency of the MobileNetV2-based model in classifying guava leaf and fruit diseases. The evaluation in this research is conducted on the basis of common metrics such as precision, accuracy, F1-score, recall support, and Matthews Correlation Coefficient. These metrics offer a complete insight into the classifying capability the model on both structured and real-world datasets. The measurements are mathematically described below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$x = \frac{(\mathrm{TP} * \mathrm{TN}) - (FP * FN)}{\sqrt{(\mathrm{TP} + \mathrm{FP})(\mathrm{TP} + \mathrm{FN})(\mathrm{TN} + \mathrm{FP})(\mathrm{TN} + \mathrm{FN})}}$$

All images in my dataset are resized to 224×224 normalization and data augmentation, with operations such as flipping, rotation, zooming, and brightness modifications. These processes mimic real scenarios and enable the model to generalize appropriately to unknown data. The model proposed utilizes MobileNetV2 for spatial and semantic feature extraction from its inverted residual blocks and linear bottlenecks. The output of the layer uses a softmax activation function to the make multi-class and classification between guava disease types. The model is light and computationally low, making it suitable for the mobile deployment and edge's computing in agricultural settings. Each dataset, BUGL2018 and Guava Fruit Disease, is separately evaluated. Post-prediction, the predictions are compared with ground truth labels, and the above-mentioned performance metrics are calculated using Scikit-learn evaluation functionality. Confusion matrices are also employed to graphically depict accurate and inaccurate classifications by class, especially for diseases like Algal Leaf Spot(ALS), Whitefly, Rust, Anthracnose, YLD, and Scorch. The combination of preprocessing, data augmentation, and a light but efficient CNN model design leads to a model that is both efficient and deployable on real-world guava disease detection applications.

4. RESULTS AND DISCUSSION

Experimental evaluation validates the efficiency of the -based convolutional neural network suggested in this research for guava Fruit disease detection. The model was MobileNetV2experimented on two different datasets: the **BU_Guava_Leaf-BUGL2018**, which has structured and balanced images with controlled conditions, and the Guava Fruit Disease Dataset, which reflects realistic field conditions with greater variability in background, lighting, and severity of disease. **The dataset divide into 80% training and testing 20% subsets**. Following preprocessing and augmentation, the model was separately trained on each dataset to test its adaptability and generality across various guava disease image types. The model had **a test accuracy of 98.14% on the BUGL2018 dataset**, reflecting high performance in the presence of clean and well-structured data. Perhaps more significantly, it had **99.30% accuracy** on the **guava Fruit disease dataset**, reflecting high robustness for real-world field-level disease detection applications. These findings validate that the MobileNetV2 model, when paired with transfer learning and real-time augmentation, is very efficient at differentiating between visually comparable guava diseases like Anthracnose, Scorch, YLD, and Insect Bite.

The comparative **accuracy results for both datasets are presented in Table 4**. As seen, the model performs highly even with heterogeneous environmental noise, class imbalance, and non-uniform image quality and is suitable for deployment in mobile-based agricultural solutions.

Dataset	No. of Classes	Training Images	Testing Images	Test Accuracy %
BUGL2018	4	2166	539	98.14%
Guava Fruit Disease Dataset	6	540,000	60,000	99.30%

Table 4. Accuracy of Proposed Model on Both Datasets

Fig. 4 demonstrates of the training and validation accuracy the MobileNetV2 model over 10 epoch's while training on the BU_Guava_Leaf dataset. The model demonstrates a consistent rise in training and validation accuracy, with convergence after the 6th epoch. This confirms that the model learns efficiently the characteristic features of guava leaf diseases without overfitting. The minor tremor in the validation accuracy is anticipated and tolerable for high-performing deep learning(DL) model's. The stability of the overall curve also confirms the robustness and generalization of the model.

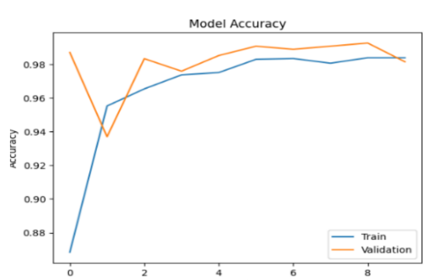

Figure 4. *Training vs Validation Accuracy of MobileNetV2 over 10 Epochs on the BU_Guava_Leaf Dataset*

The classification performance of the model is effectively visualized using the confusion matrix shown in Fig. 5. This matrix clearly highlights the number of correct and incorrect predictions for each disease class in the BU_Guava_Leaf (BUGL2018) dataset. As seen in the figure, the model performs exceptionally well across all four classes, with only minor misclassifications observed between similar categories such as **Healthy Leaf** and **Whitefly**. The highest performance was achieved for the Rust and Algal Leaf Spot classes, where almost all test samples were correctly classified. The dominance along the diagonal of the matrix validates the robustness and precision of the models in differentiating various classes of guava leaf disease.

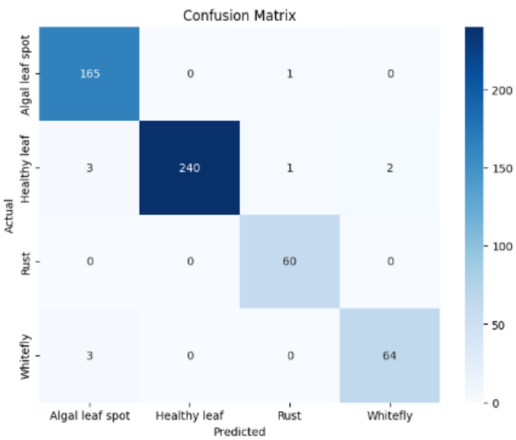

Figure 5. Confusion Matrix of MobileNetV2 Predictions on the BU_Guava_Leaf Dataset

In order to further assess the performance of the model for each class of diseases, Fig. 6 displays a classification report for the BU_Guava_Leaf test set. From the results, it is evident that there is high precision, recall, and F1-score for all classes. This validates the reliability of the model. The results indicate that both Rust and Healthy Leaf have close to perfect recall scores, as the MobileNetV2 model classified almost all instances correctly. The same is true for Algal Leaf Spot and Whitefly, as there is high precision. This implies a low number of false positives. The results are also supported by a high weighted macro value of 0.98, which validates the performance of the model in generalizing different types of diseases.

```
Classification Report:
                 precision    recall  f1-score   support

Algal leaf spot       0.96      0.99      0.98       166
   Healthy leaf       1.00      0.98      0.99       246
           Rust       0.97      1.00      0.98        60
       Whitefly       0.97      0.96      0.96        67

       accuracy                           0.98       539
      macro avg       0.98      0.98      0.98       539
   weighted avg       0.98      0.98      0.98       539
```

Figure 6. Classification Report on BU_Guava_Leaf Dataset

In order to validate the performance of the proposed MobileNetV2 model, the accuracy level is compared with a few popular deep learning architectures, as mentioned in the existing literature. Table 5 represents the comparison chart, focusing on the datasets, the proposed model, accuracy level, and the advantages and disadvantages of the respective architectures. It is quite evident from the comparison results that the proposed MobileNetV2 model has the capability to achieve a competitive level of accuracy with less computational complexity, making it more suitable for real-time applications.

Study	Dataset	Model	Accuracy (%)	Advantages	Limitations
Mohanty et al. [9]	Synthetic (PlantVillage)	Basic CNN	99.35	High accuracy under controlled conditions	Poor generalization to real field images
Barbedo [10]	Realistic Images	CNN / Segmentation	~90	Focused on natural variability and noise	Limited scalability to large datasets
Too et al. [11]	Mixed	ResNet, VGG, Inception	95–98	Tested multiple architectures	Computationally expensive, heavy models
Howard et al. [12]	Benchmark	MobileNet	94–96	Lightweight, efficient for mobile use	Slightly reduced accuracy vs larger CNNs
Sharma et al. [14]	Fruit Dataset (Real)	MobileNet	96.47	Real-time inference on mobile devices	Limited dataset diversity
Saleem et al. [16]	Local Guava Dataset	ResNet, SqueezeNet	97.74	High accuracy for guava disease detection	Model too large for real-time use
Yadav et al. [17]	Real Guava Leaves	CNN	95.82	Trained on field images	Did not explore lightweight models
Proposed Study	BUGL2018 + Guava Fruit Disease	MobileNetV2	~99	High accuracy, efficient, suitable for mobile/edge deployment	suitable for mobile/edge deployment Requires further validation on large-scale real-field data

Table 5: Comparison of existing methods and the proposed MobileNetV2 model for guava disease detection.

Figure 7 Correctly classified images of the BU_Guava_Leaf test set for visualization of the model's prediction ability, along with the ground truth and predicted class label for each test image. As seen, the model is successfully able to classify between different kinds of diseases, including whitefly, rust, algal leaf spot, and healthy leaf, which are quite similar in nature.

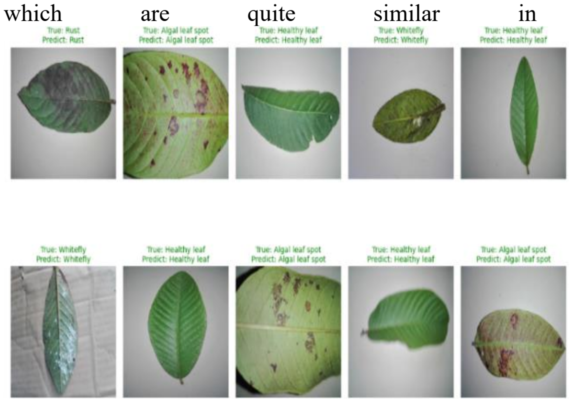

Figure 7 shows the correctly classified images of the test set of BU_Guava_Leaf

5. CONCLUSIONS

This research presented a deep learning-based framework for guava leaf and fruit diseases, which was implemented by utilizing the MobileNetV2 architecture for the detection of guava leaf and fruit diseases. The proposed framework was trained and tested on two datasets: BU_Guava_Leaf (BUGL2018), which represented a structured dataset, and the Guava Fruit Disease Dataset, which represented a real-world dataset, and it showed promising results for both datasets. The lightweight MobileNetV2 architecture, along with preprocessing and data augmentation techniques and transfer learning, successfully learned discriminative features for guava leaf and fruit diseases while maintaining its efficiency for deployment on mobile devices. The performance of the proposed framework was validated by evaluating its precision, recall, and F1-score, which showed its consistency and accuracy for the detection of guava leaf and fruit diseases. The proposed framework is useful for smart agriculture, and its future work may be conducted for its expansion and deployment as a mobile application for the detection of guava leaf and fruit diseases.

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