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Prediction of Grape Disease using Deep Learning based on MobileNetV2 and Explainable AI with Grad-CAM for Disease Management

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Abstract: *The grapes production can be affected by diseases that cause changes to the look and state of the leaves and may reduce the quality of the crop if the disease are not detected in time. Even though visual diagnosis is of some help, it depends on the operator's experience and can become difficult when different diseases show similar symptoms.*

The study presents an image-based approach for predicting and Gradient-weighted Class Activation Mapping (Grad-CAM) for providing a visual explanation. The System can detect four kinds of disease: Black Measles, Black Rot, Healthy, and Isariopsis Leaf Spot. The model produces a distribution of class probabilities and Grad-CAM is used to highlight the parts of the image that are related to the predicted class.

A general module based on knowledge then provides information regarding the symptoms, advice on how to manage the disease, and preventive measures for the disease which has been predicted. Having been tested on 903 images, the system achieved 886 correct predictions and 17 incorrect ones, giving an accuracy of 98.12%, a weighted precision of 98.13%,a weighted recall of 98.12%, and a weighted F1-score of 98.12%. The errors that were seen were mostly between Black Measles and Black Rot. The study therefore incorporates prediction, visual explanation, and disease-management information into one workflow, while at the same time recognizing the need for further validation with a wider variety of field images..

Keywords: the classification of grape diseases, MobileNetV2, deep learning, explainable artificial intelligence, Grad-CAM, the detection of plant diseases, computer vision, image processing, and disease management

I. INTRODUCTION

Plant diseases are a major concern in agriculture because if they are not recognized early then the infection can spread and damage the health of the crops. Research carried out so far in the field of computer vision has demonstrated that deep learning is able to learn visual patterns associated with disease directly from images of leaves, enabling the automatic identification of plant diseases. It has also been found that high performance on controlled images does not necessarily mean that the Grapevines are appropriate for analysis based on images since many of the symptoms of disease can be observed on the leaves. Recent studies focusing on grapes have examined convolutional neural networks, lightweight architectures, and vision transformers with a view to classifying grape leaves. MobileNetV2 is especially attractive in situations where the system is expected to operate with limited computational resources since this architecture employs inverted residual blocks and lightweight deptwise convolutions, providing a good compromise between accuracy and efficiency. Another issue is interpretability; a classifier may assign a disease label

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with high confidence without showing the visual evidence on which the decision is based. In recent work on plant diseases, Grad-CAM has been used to verify whether the models focus on the relevant parts of the leaves. The current study goes beyond this by implementing a complete workflow rather than treating classification and explanation as two separate tasks. The system takes a picture of a grape leaf, carries out preprocessing, uses MobileNetV2 to predict one of four classes, generates a Grad-CAM explanation, and then shows the specific symptoms of the disease, general management, and prevention advice.

Objectives

The main objectives are:

• To train an automated system for classifying grape leaf diseases and to use MobileNetV2 as the classification network. The diseases to be classified are Black Measles, Black Rot, and Healthy, Isariopsis Leaf Spot. The models accuracy, precision, recall, F1-Score and confusion matrix should be assessed; Grad-CAM should be used to provide a visual explanation, this explanation should be given, and the predictions should be linked to the symptoms, general management information and prevention advice.

II. LITERATURE REVIEW

[1] Mohanty and others demonstrated that deep convolutional networks can be employed to classify leaf diseases from images of plants, making use of a large public data set; their study established the possibility of recognizing plant diseases from images and pointed out the gap that existed between their work and the current state of the art, while stressing the difference between controlled and external datasets.

[2] Ferentions developed deep learning models for the purpose of diagnosing plant diseases using a large open image dataset containing various plat species. The study looked at the different combinations of plant species and diseases. It demonstrated the high performance and the significance of CNN-based image analysis, with an emphasis on automated diagnosis.

[3] Lin and others have developed a lightweight convolutional neural network for the purpose of identifying diseases in grape leaves, naming it GrapeNet. In their experiments they tested a number of established architectures such as MobileNetV2 and also used grad-cam in order to visualize the models attention; this is indeed a very special piece of work.

[4] Kunduracioglu and pacal applied a wide variety of CNN and vision-transformer models to the task of classifying grape leaves and detecting diseases. In doing so, the researchers used transfer learning with images of grapes from the PlatVillage database and with a separate grapevine data set, showing the considerable potential of transfer learning. They also developed new visual models and methods for learning about grapes.

[5] A study carried out by IEEE in 2025 examined in detail the real-time detection of grape leaf disease with the use of MobileNetV2 and arrived at the same conclusions. The project includes four categories: Black Measles, Black Rot, Isariopsis Leaf Spot, and Healthy. This makes it a particularly relevant research reference for the chosen architecture and problem solving.

[6] Venkatachalam et al. used EfficientNetV2L, data augmentation and Grad-CAM in order to diagnose disease in grape leaves. Their study supports the use of visual explanations in combination with the deep learning-based classification of grape diseases.

[7] Gopalan et al. applied ResNet152 in conjunction with Grad-CAM for the diagnosis of corn leaf diseases. The crop and the model type are not being used, although they could be. Despite the fact that their results differ, the study does demonstrate the value of visual explanations for use in plant disease applications.

[8] Murugesan and others investigated a hybrid deep-learning system for classifying crop leaf diseases into several categories, as shown in Figure 3. They also stress the importance of assessing the interpretability of the model together with its predictive ability.

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[9] Zed and others looked at the detection of diseases in strawberries and grapes in real-world field conditions. The study points out that the following variations occur in the environment, the lighting, and the imaging, which are important aspects for practical deployment.

[10] Kumar and Sharma have developed a mobile application which employs MobileNetV2 for the real-time detection of various crop diseases. The system takes into account five types of crops (one of which is grape) and 25 different disease/healthy categories. Although the study does not remain limited to an experimental environment, it demonstrates the practical use of a lightweight MobileNetV2 model in a real-world, user-facing application.

Research Gap

The available literature shows that there has been a great deal of progress in the automated classification of plant and grape diseases, but practical systems still face three closely related problems. On the one hand, merely attaining a high degree of classification accuracy does not provide an explanation as to why a specific class was chosen by the model. On the other hand, explainability is usually examined separately from the final users workflow. Moreover, images taken in the real world can differ from those in controlled datasets because of variations in lighting, angle of view, background, and environment. In this study the first two of these problems are dealt with by combining MobileNetV2 with Grad-CAM and by incorporating a disease-information module. The paper also clearly recognizes that field validation is a limitation and something that will need to be addressed in the future.

III. METHODOLOGY

The system is based on sequential evaluation of images. The input is a grape leaf image standardized in the same way as during the model training and then classified using MobileNetV2, explained using Grad-CAM, and finally linked to relevant disease management information.

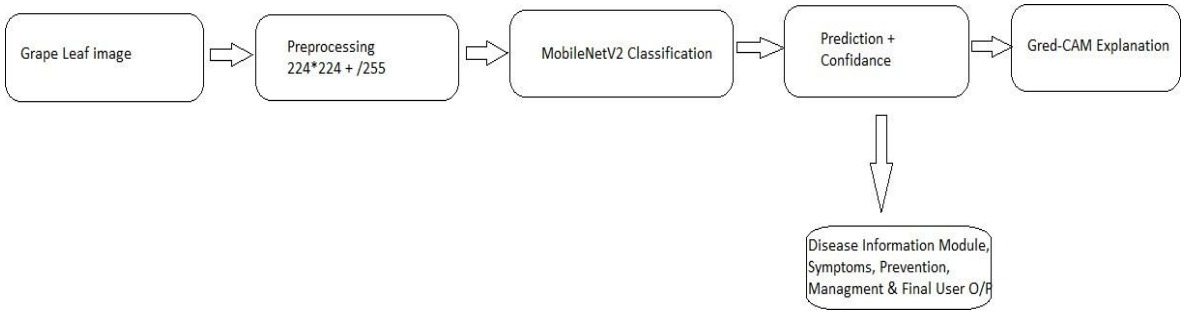


Figure 1: Overall workflow of the proposed grape disease prediction framework.

Input and Image Preprocessing

The input image is resized to 224*224 pixels. The pixel values are converted to float numbers and divided by 255. The normalized range is about 0 to 1. This pre-processing style is said to be the same as that applied to the trained model. The standardized image is represented as a tensor and sent into the classifier. The model does not get a disease label throughout the whole inference process, but the class is chosen according to the distribution of predicted probabilities.

MobileNetV2 Classifier

We chose MobileNetV2 as the final architecture for classification. The original MobileNetV2 architecture employs inverted residual blocks and linear bottlenecks in conjunction with depthwise convolutions, a property that makes it suitable for efficient visual interface. The final outputs of the executed model are 4 probabilities of classes. The category with the highest likelihood is then selected as the predicted class for a given input image. For one of the analyzed images the probability of Black Rot was 97.53%, while Black Measles, Healthy and Isariopsis Leaf Spot were 0.24%, 1.33% and 0.90% respectively.

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For example, one test image produced:

Class	Probability
Black Measles	0.24%
Black Rot	97.53%
Healthy	1.33%
Isariopsis Leaf Spot	0.90%

The highest probability corresponds to Black Rot.

Model Configuration

Parameter value used MobileNetV2 Input size 224*224*3 Number of Output class 4 Target Grad-CAM layer out_relu Normalization Features map size: 7*7*1280 pixel intensity/255 Create a probability distribution over 4 classes.

Explainable AI using Grad-CAM

This study adopted Grad-CAM as the elucidation methodology. This method evaluates the importance of different spatial regions in a convolutional feature map using the gradients relative to the predicted class. We implemented MobileNetV2 which has a final convolutional layer of spatial size 7*7 and 1280 channels.

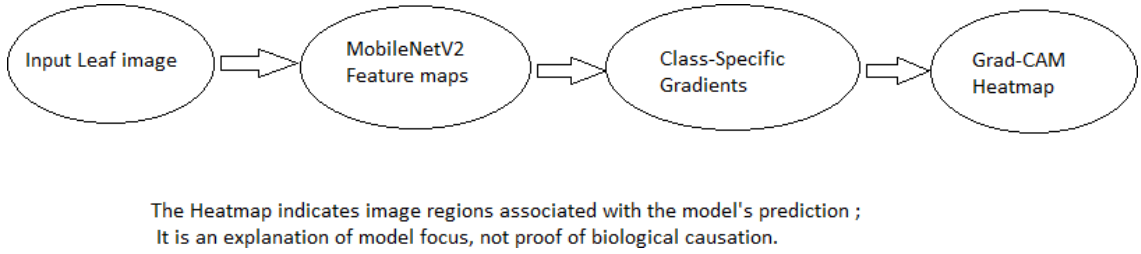


Figure 2: Conceptual process of Grad-CAM as used in proposed system

The Grad-CAM method calculates the gradients specific to each class, averages these gradients across the spatial dimensions to obtain the channel weights, and then combines them.

Disease Management Recommendation

After the items have been categorized, the predicted category is used to obtain information from the systems disease-information module; for each disease that is supported, the module includes the following: symptoms, Management, and Prevention. For example, concerning Black Rot the system will give information regarding the removal of infected plant material, about improving canopy ventilation, about avoiding prolonged leaf wetness, and about following the correct disease-management advice. The section containing the recommendations is intended to offer general supportive information and not act as a substitute for advice from a qualified agricultural professional.

Dataset and Experimental setup

The images used in this experiment were made up of 903 images which were divided among four classes.

Class	Test Images
Black Measles	239
Black Rot	228
Healthy	217
Isariopsis Leaf Spot	219
Total	903

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The trained MobileNetV2 model was used to evaluate the test dataset. The evaluation used:

- Accuracy
- Precision
- Recall
- F1-score
- Classification report
- Confusion matrix

Evaluation Metrics

Accuracy is the number of images which are correctly classified divided by the total number of images that are examined. Precision refers to the number of times that the predictions for a class are correct, while recall shows how many of the images in that class were successfully identified.

The F1-score involves the harmonic mean of precision and recall; in the class of multiclass evaluation, the study also provides weighted precision, weighted recall, and a weighted F1-score together with the class –wise figures. These values are then used in the confusion matrix to identify the classes that result in classification errors.

Overall result

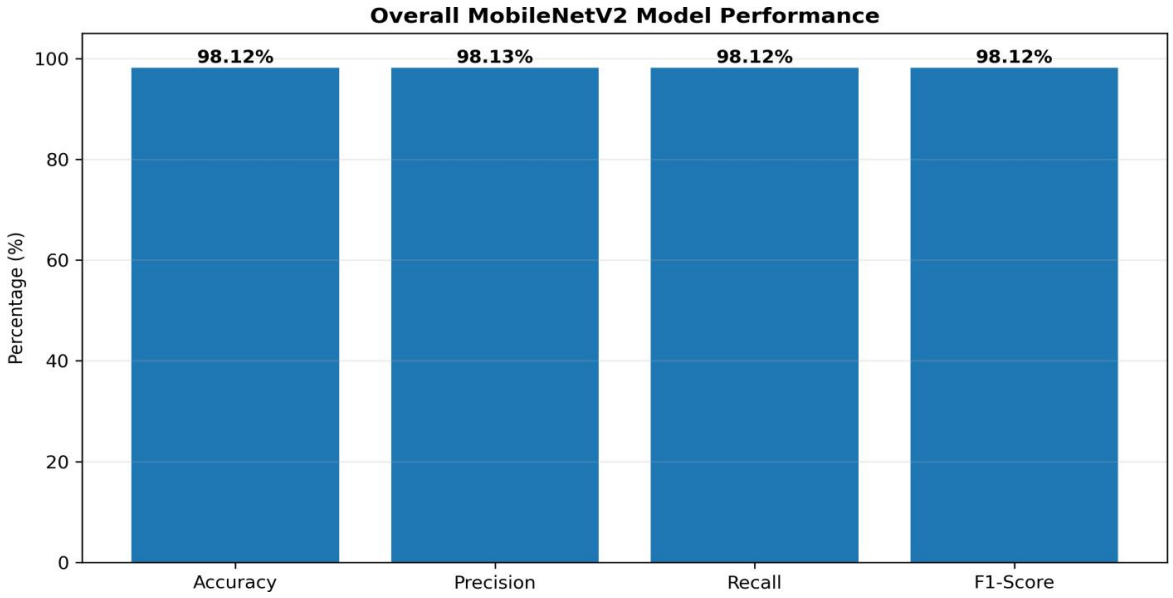


Figure 3: Overall accuracy of the MobileNetV2 model tested on the test set.

The model achieved an accuracy of 886 out of 903 on the test images. Seventeen additional images were misclassified. The result was accurate with 98.12% accuracy, 98.13% weighted precision, 98.12% weighted recall and 98.12% weighted F1-score.

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Class-wise Results and Errors Analysis

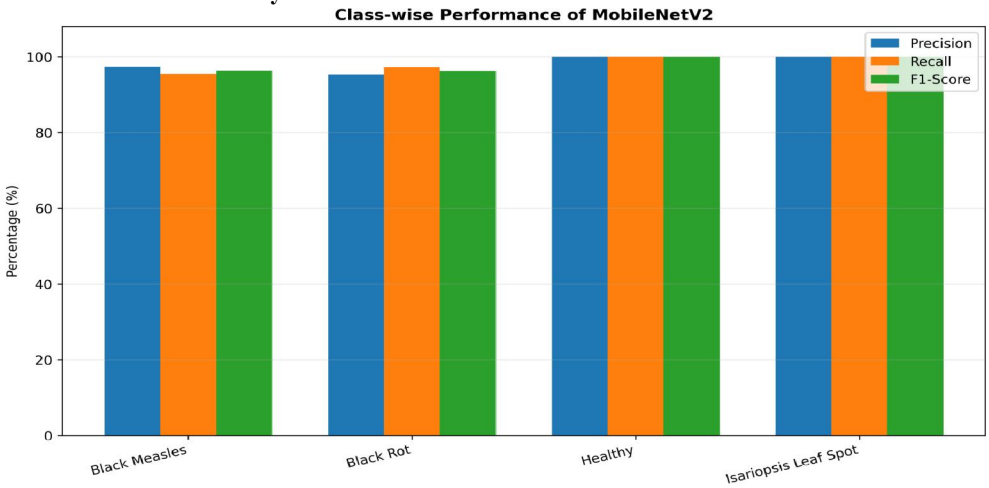


Figure 4: Precision, Recall, and F1-score for the four grape leaf classes

Class-wise performance:

Class	Precision	Recall	F1-score	Support
Black Measles	97.44%	95.40%	96.41%	239
Black Rot	95.28%	97.37%	96.31%	228
Healthy	100.00%	100.00%	100.00%	217
Isariopsis Leaf Spot	100.00%	100.00%	100.00%	219

Confusion Matrix

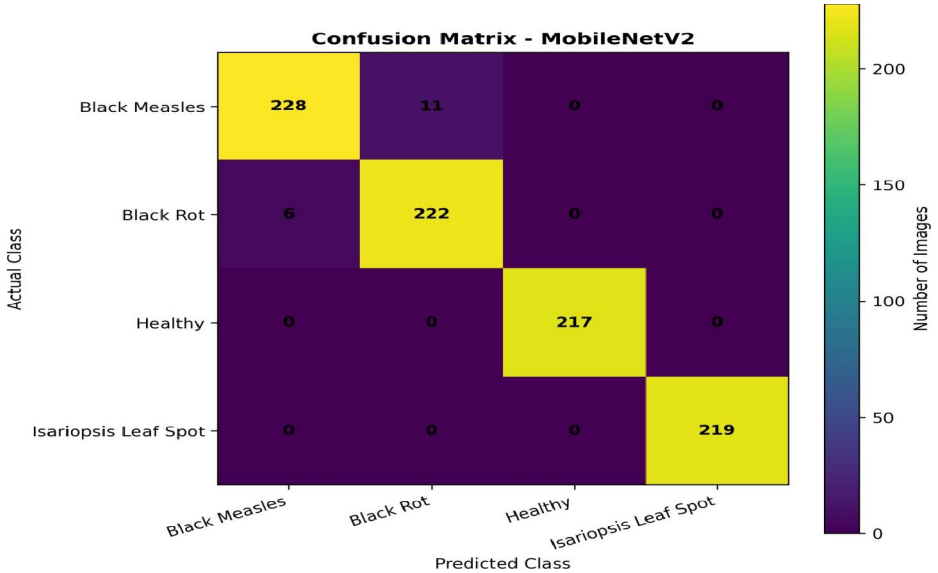


Figure 5: Confusion matrix of the evaluated test set.

Confusion matrix represents the accuracy of classification of 228 Black Measles images and 222 Black Rot images. The visuals of measles were predicted to look like Black Rot. The expected visuals of Black Rot were six pictures of

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Black Measles. For Isariopsis Leaf Spot classes no false predictions were detected in the evaluated test set. Therefore, the majority of the 17 errors found were focused on the visual correlation between the two classes of disease.

Discussion

The results show that MobileNetV2 was able to learn visual patterns that are useful for the four grape leaf classes that it was trained on. The obtained accuracy of 98.12% is good achievement for the dataset tested, but the class specific results are more informative than only accuracy. The only errors noted were for Black Measles and Black Rot, probably because they look so similar. This rest set includes a classification task. The quantitative performance indicators lack an interpretative dimension; Grad-CAM adds this layer of interpretability. In case of a classification score, the question concerns which class the model chose and how confidant the model was about this choice. Grad-CAM output provides a visualization of areas which are correlated with this decision. It means that the model is very confident that the image belongs to the cat class. The management module redesigns the user experience from being a simple classifier to a small decision support workflow. However, the recommendations provided are quite general and cannot be seen as personalized prescriptions. Local conditions, crop stage, disease severity, and expert's opinion should help to make the decision about the deployment, whether the treatment is needed, and which one is the best.

Limitations

Currently, the application is limited by four classes. Metrics depend on the test set that is used, and the evaluation is made based on this set. They cannot be seen as guarantees of the performance on any field images. Difference in lighting can be seen in vineyard images, and the evaluation data may not be equally distributed by background, camera angle, leaf overlap, or disease severity. Treatment module does not provide personalized recommendations validated by experts but general information instead. Finally, Grad-CAM describes the models visual focus and cannot be seen as the proof of the biological causality.

Future Scope

Future research can include expanding the disease list, gathering more field images, making external validation in other regions, and making some modifications. Further developments can include the deployment of mobile/web applications, adding regional language support, using environmental/weather data, and improvement of management module by using expert agricultural knowledge. Explainable AI methods such as Grad-CAM++, SHAP, and others should also be considered.

IV. CONCLUSION

The goal of this research was to create an explainable framework for predicting grape leaf diseases based on MobileNetV2, Grad-CAM, and disease-information modules. The system can distinguish four classes – Black Measles, Black Rot, Healthy, and Isariopsis Leaf Spot from grape leaf images. On the test set containing 903 images, the model managed to correctly classify 886 cases which means the accuracy of 98.12% on the implementation set. The obtained results show high accuracy (98.13%), weighted precision (98.12%), weighted recall (98.12%), and weighted F1-score (98.12%). One of the main contributions of this work is the combination of three functions – disease prediction, visual explanation, and disease management information. MobileNetV2 provides the classification outputs, Grad-CAM provides the visual explanation of the prediction, and the knowledge-based module provides the symptoms, overall management and prevention tips. In the test set used, only the errors associated with Black Measles and Black Rot were found. From the obtained results, it can be said that the proposed framework is a promising prototype for an explainable analysis of grape diseases. However, further tests are required before the framework could be declared practically applicable in the field.

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