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USING CONVOLUTIONAL NEURAL NETWORK FOR GRAPE PLANT DISEASE CLASSIFICATION

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Abstract: Plant disease classification is the use of machine learning techniques for determining the type of disease from the input leaf images of the plants based on certain features. It is an important research area since early identification and treatment of plant disease is critical for saving crops, preventing agricultural disasters, and improving productivity in agriculture. This study proposes a new convolutional neural network model that accurately classifies the diseases on the plant leaves for the agriculture sectors. It especially works on the classification of plant diseases for grape leaves from images by designing a deep-learning architecture. A web application was also implemented to help the agricultural workers. The experiments carried out on real-world images showed that a significant improvement (8.7%) on average was achieved by the proposed model (98.53%) against the state-of-the-art models (89.84%) in terms of accuracy.

Keywords: Deep Learning, Convolutional Neural Network, Image Classification, Agriculture, Grape, Plant Disease

Evrişimli Sinir Ağının Üzüm Bitkisi Hastalık Sınıflandırması için Kullanılması

Öz: Bitki hastalık sınıflandırması, belirli özelliklere dayalı olarak bitkilerin yaprak görüntülerinden hastalık türünün belirlenmesi için makine öğrenmesi tekniklerinin kullanılmasıdır. Bitki hastalıklarının erken teşhisi ve tedavisi, ekinleri kurtarmak, tarımsal felaketleri önlemek ve tarımda verimliliği artırmak için kritik olduğundan, önemli bir araştırma alanıdır. Bu çalışma, tarım sektörü için bitki yapraklarındaki hastalıkları doğru bir şekilde sınıflandıran yeni bir evrişimli sinir ağı modeli önermektedir. Bir derin öğrenme mimarisi tasarlayarak özellikle üzüm yapraklarındaki hastalıkların sınıflandırılması üzerine çalışmaktadır. Tarım işçilerine yardımcı olması için bir web uygulaması da geliştirilmiştir. Gerçek dünya görüntüleri üzerinde yapılan denemeler, önerilen modelin (%98,53) doğruluk açısından son teknoloji modellere (%89,84) göre ortalamada önemli bir iyileştirme (%8,7) sağladığını göstermiştir.

Anahtar Kelimeler: Derin Öğrenme, Evrişimli Sinir Ağı, Görüntü Sınıflandırma, Tarım, Üzüm, Bitki Hastalığı

1. INTRODUCTION

Plant disease is a significant problem in agriculture since it directly reduces the quantity and quality of plant production. These diseases could have a huge impact on the economy negatively in the global agricultural industry (Chadha et al., 2021). Plant diseases are likely to have a detrimental impact on various plant processes such as plant growth, absorption of nutrients,

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photosynthesis, and fruit development. Therefore, early identification and treatment of plant disease are critical for saving crops, preventing agricultural disasters, and improving productivity by maximizing yield, and this is where machine learning (ML) techniques may help farmers and offer advantages over traditional methods.

The main causes of plant disease are pathogenic microorganisms (i.e., fungi, bacteria, and viruses), insects, environmental conditions (i.e., temperature, soil type, and humidity), and disasters (i.e., drought and flood) (McBeath and McBeath, 2010). These various causes lead to different visual symptoms like yellowing, necrosis, or black spots, mainly on the plant leaves. Thus, image classification is the key process of plant disease detection and its severity if required.

Plant disease classification is a vital research area in machine learning (Ahmed and Yadav, 2023). It is the process of determining the type of disease from the input leaf image of the plant based on certain features. ML-based solutions for plant disease detection have utilized various classification techniques (Jeyalakshmi and Radha, 2020; Swetha and Jayaram, 2019). In other words, this technology uses computer vision-based solutions to classify plant leaf images that are prone to pests and diseases. An automatic detection system that can identify the conditions of the plants from leaf images will be of great use to agricultural workers or anyone interested in plant cultivation. With such an automated system, the detection and identification of the disease could take less time and effort for people who could have limited access to any facilities or laboratories that identify diseases using chemistry or biology (Singh and Misra, 2017). As a result, an early detection system based on a machine learning model will immediately alert them before the disease spreads over the whole plant.

Deep learning (DL) is a recently emerging field of machine learning that can efficiently handle complex problems with a variety of data types like images and videos (Shrestha and Mahmood, 2019). For the plant disease classification, Wagle and Harikrishnan (2021) showed that deep learning methods could achieve higher accuracy compared with traditional ML methods such as support vector machines. As one of the DL techniques, the convolutional neural network (CNN) is popular due to its ability to automatically learn problem-specific features and useful representations from images. With this motivation, this study used the CNN technique as the principal detector for plant disease classification.

The main contributions of this paper can be listed as follows. (i) It proposes a new deep-learning-based model to classify diseases in plants. (ii) It especially identifies the grape plant diseases from the leaf images by designing a CNN architecture. (iii) The experiments carried out on a real-world dataset showed that the proposed model (98.53%) outperformed the state-of-the-art models (89.84%) in terms of accuracy.

2. RELATED WORK

Manual identification of diseases in plants by humans is a time-consuming process and is limited to small areas. It highly depends on the ability of humans, resulting in less accuracy (Prajna, 2021) because the diseases can be very diverse due to the variety of plants. Since climate changes and global warming dynamically affect the types of diseases, even experts could not be familiar and the results could be a failure of detection of particular diseases. Thus, it is significant to design a smart intelligent system that will help to identify plant diseases correctly and automatically. Especially, a mobile application can help farmers to detect disease in a crop by capturing an image of the plant leaf in the field, and they will get a fast and accurate result on the spot. Similarly, a drone can visit the whole field and monitor the health of the plants. Based on the results of mobile and drone applications, the farmers can develop proper strategies and identify potential solutions to improve crop productivity. An automated ML-based solution can reduce the use of extra pesticides, and farmers can get a good profit with improved agricultural outputs, being more beneficial for the economy of the country.

The studies in the literature regarding plant disease detection can be mainly categorized into two groups. The first group is the use of traditional machine learning methods such as support vector machine (SVM), k-nearest neighbors (KNN), and decision tree (DT) on features (i.e., color features, geographic features) extracted from image data for disease identification. The second group is to directly use the plant image dataset for the classification of diseases using a deep learning technique with automatic feature extraction.

In the first category, computer vision-based solutions (Singh et al., 2020) were proposed that used machine learning techniques for accurate identification of plant disease at early stages. Swetha and Jayaram (2019) used SVM, DT, KNN, random forest (RF), logistic regression (LR), and naive Bayes (NB) as the recognition system to predict grape leaf diseases. They achieved the highest accuracy with RF (86%). Monowar et al. (2022) were able to achieve an 88.90% prediction rate in grapes using the bootstrap your own latent (BYOL) method.

In the second category, some efforts (Monowar et al., 2022; Ahil et al., 2021) have been made that used deep learning techniques to improve prediction performance in the classification of plant diseases. Ghosh and Roy (2021) proposed a CNN model for automated disease detection tasks from grape leaf images. The overall efficiency of their model was 91.96%.

Recently, machine learning methods have been used for disease classification in different plants such as apples (Ahil et al., 2021; Kaur and Sharma, 2022), strawberries (Wagle and Harikrishnan, 2021), tomatoes (Thenmozhi et al., 2021), corn (Nagi and Tripathy, 2023; Joshi et al., 2022), banana (Suo et al., 2022), potato (He et al., 2022), peach (Monowar et al., 2022), cherry (Suo et al., 2022), pepper (Kurmi and Gangwar, 2021), and citrus (Monowar et al., 2022). Our study aims to classify diseases for grape plants due to their varied and large-scale uses.

Improvements in detection technologies could be a valuable asset or an advantage for early intervention to avoid wild and widespread diseases, minimize the destruction, and conserve the overall health of plants. For these reasons, this study aims to detect and identify plant leaf diseases by using classification techniques.

The main uncertainty in a deep learning study is the design of CNN architecture that could yield a high performance. This study aims to design and develop an effective CNN architecture that provides robust and reliable predictions for grape plants.

3. MATERIAL AND METHODS

This study aims to propose a deep learning-based model to classify diseases in grape plants using the images of leaves. A new CNN architecture was designed for plant leaf disease classification. The main purpose is to develop an effective model to provide reliable and robust predictions.

3.1. Dataset Description and Data Preprocess

In this study, the dataset, which contains the grape disease images, was obtained from the PlantVillage dataset (Hughes and Salathe, 2015). It includes 3251 images of grape leaves divided into four categories: healthy, isariopsis leaf spot, esca, and black rot. Sample grape leaf images belonging to different categories are shown in Figure 1. The images in the dataset are of size 256 × 256 × 3.

The proposed method executes resizing and rescaling operations as data pre-processing to improve the ability of the algorithm to capture important features in images. In the first phase of pre-processing, input images were resized by protecting the aspect ratio. As the next step, a normalization operation was performed, which calculates every value in the image by scaling with 1/255 to have the same distribution all over the output. In this way, the scaling operation converted each pixel value in the range 0-255 to values in the range 0-1.

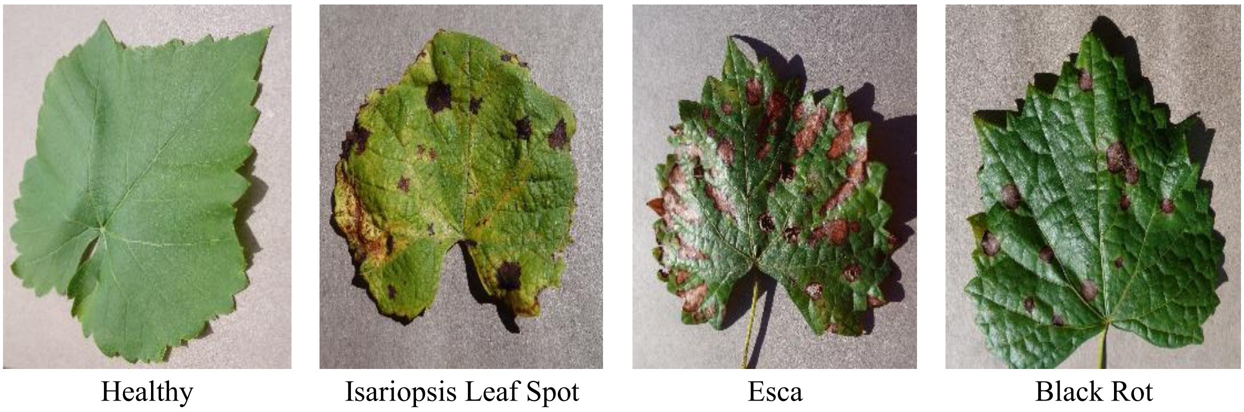

Figure 1:
Sample images for grape leaf diseases

3.2. Proposed Approach

Figure 2 shows an overview of the proposed system. In the first step, the grape leaf images are acquired by digital cameras for all classes. The dataset contains different disease images and their corresponding labels. In the data preprocessing step, resizing and rescaling operations are performed for images to improve efficiency. Afterward, the dataset is divided into training, validation, and testing sets. In the next step, a convolutional neural network architecture is trained for the multiple numbers of epochs on images of plant leaves. After that, the performance of the trained model is evaluated at a set of criteria such as accuracy, precision, recall, and f-score. In the classification step, the deep learning model identifies diseases on the image that the model has not seen before.

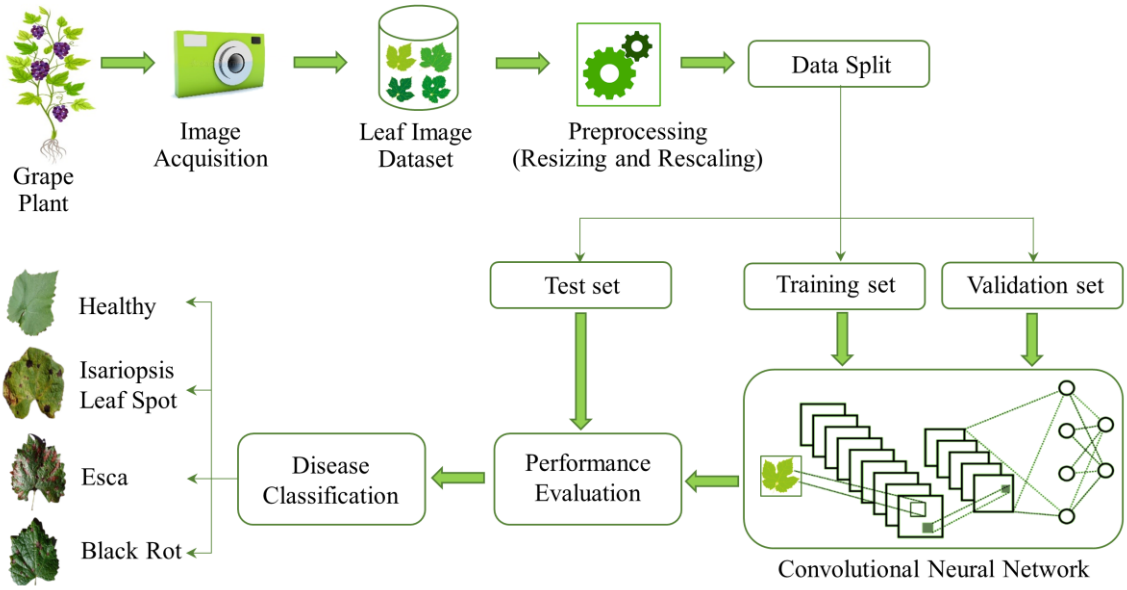

Figure 2:
An overview of the proposed approach

Real-time observation of plant disease by a human in a large field area is a big challenge, requiring experience, time-consuming, and costly. For this reason, in this study, a deep-learning method was used to construct an automated model for the identification of grape plant diseases.

Especially, we have considered the CNN method as the principal detector to benefit from its ability of automatic feature extraction and high classification performance.

Figure 3 displays the proposed CNN architecture, which consists of convolution layers with filters and rectified linear units (ReLU) activations, max-pooling layers, a dropout layer, a flatten layer, followed by dense fully-connected layers, and an output layer. The convolution layer performs feature extraction on the input image through kernel sliding. The pooling layer is responsible for reducing the dimensionality of the data. The dropout layer is used to deactivate some randomly selected nodes to prevent over-fitting. The flatten layer converts the multidimensional data into a one-dimensional array. Finally, the fully connected layer integrates the information and the output layer is used to classify.

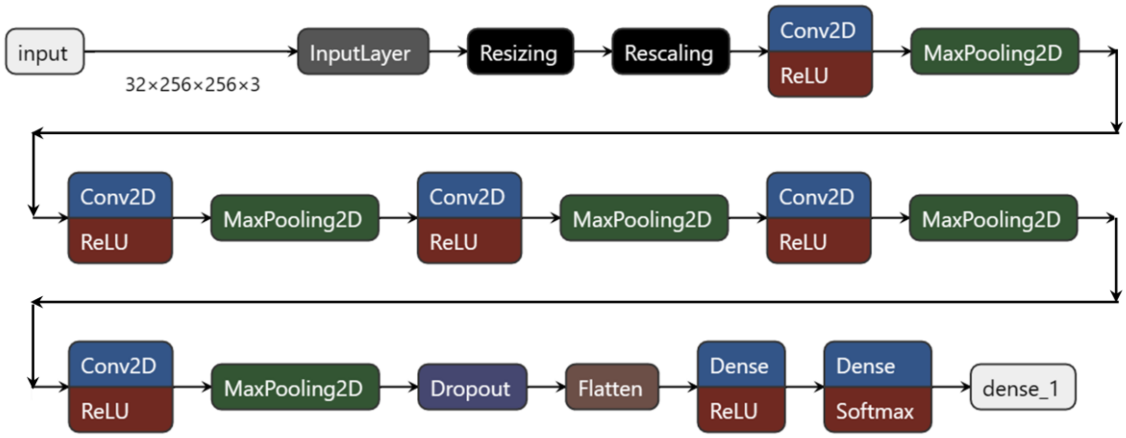

Figure 3:
Proposed CNN architecture for plant leaf disease detection

3.3. Web Application

In this study, a web application was implemented using Python and supported libraries to help farmers or people who plant for hobbies. The main focus is on classifying the diseases from the grape plant leaves. It could be used to classify diseases and learn how to act, protect, and improve plant health. Such a leaf disease detection application could have a significantly important role in the early stages. It could provide benefits to the users to acknowledge diseases and their possible impacts on plants. A screenshot of the application is shown in Figure 4. The uploaded image is processed at the backend with the trained model for disease prediction and output is displayed with a certainty percentage, predicted disease name, and suggestion for treatment.

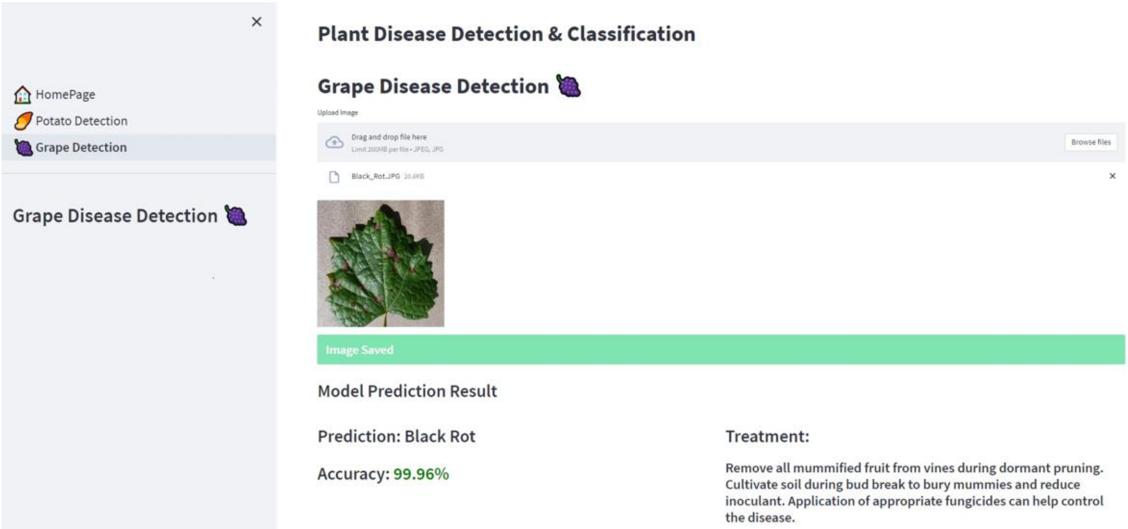

Figure 4:
The user interface of the web application

4. EXPERIMENTAL RESULTS

The proposed CNN model was trained, validated, and tested using grape leaf images. The dataset is divided into three sets: training (80%), validation (10%), and testing (10%). The proposed model achieved 98.96% accuracy and 3.05% loss in training, 99.37% accuracy, and 2.58% loss in the validation set. In the test set, it obtained 98.53% accuracy and 4.21% loss for grape disease detection. Table 1 shows the observed precision, recall, and f-score values for each class separately. The macro averages and weighted averages are over 0.977, so they are very close to 1, meaning that the model is reliable. The f-score ranges between 0.972 and 0.995, meaning that the method does return few errors.

Table 1. The performance results of the proposed model

Grape Leaf Disease	Precision	Recall	F-score
Black Rot	0.988506	0.955556	0.971751
Esca	0.991935	0.991935	0.991935
Healthy	0.939394	1.000000	0.968750
Isariopsis Leaf Spot	0.989474	1.000000	0.994709
Macro Average	0.977327	0.986873	0.981786
Weighted Average	0.985538	0.985251	0.985226

Table 2 represents the confusion matrix which summarizes the incorrect and correct predictions of the classifier with count values. Diagonal cells of the matrix indicate the number of correct predictions and the non-diagonal elements refer to the number of incorrect predictions. Note particularly that [86, 123, 31, 94] are the diagonal elements of the confusion matrix, therefore, these high values confirm the high performance of the proposed model for classifying grape plant diseases. As can be seen, the trained model usually had no difficulty in classifying all disease types. For example, 86 out of 87 black-rot diseases were predicted accurately; however, only 1 of them was misclassified by the model. The results confirmed the high robustness of the proposed model in predicting grape plant diseases.

Table 2. Confusion matrix obtained for grape disease classification

	Black Rot	Esca	Healthy	Isariopsis Leaf Spot
Black Rot	86	1	0	0
Esca	1	123	0	0
Healthy	2	0	31	0
Isariopsis Leaf Spot	1	0	0	94

Figure 5 shows sample grape leaf images that are randomly taken from the data and classified by the proposed model. It can be seen that the trained model can correctly predict grape leaf diseases. For example, the disease in the first sample leaf image was identified accurately with 98.4% certainty. Similarly, the second sample image was labeled correctly with a high (99.93%) probability.

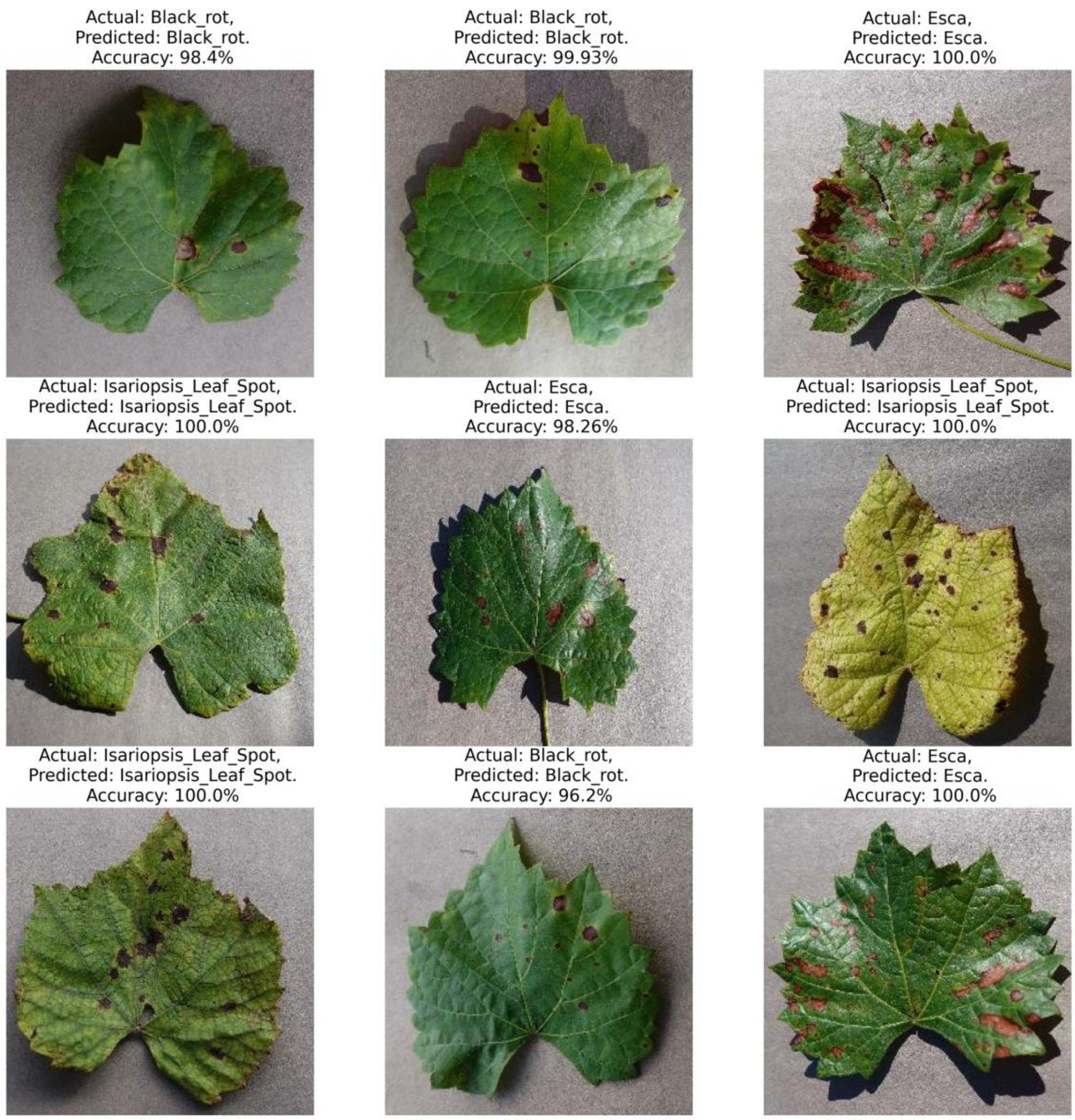

Figure 5:
Sample prediction results for grape leaves

Table 3 presents the results of state-of-the-art studies that reported for the same dataset. As can be seen, our model (98.53%) outperformed the previous models (89.84%) on average. Thus, it demonstrated its superiority over the existing models with an 8.7% improvement. For instance, it performed better than the traditional machine learning methods such as decision tree (78.00%) (Swetha and Jayaram, 2019), naive Bayes (81.87%) (Jeyalakshmi and Radha, 2020), k-nearest neighbors (90.00%) (Adeel et al., 2019), and linear regression (70.00%) (Swetha and Jayaram, 2019). It is observed that the most widely used method is the support vector machine (SVM) in the previous studies. As reported in the table, our model achieved higher performance than the previous SVM-based models. In addition, Tarannum et al. (2017) obtained 94.00% accuracy with SVM, while we achieved 98.53% accuracy on the same dataset. Consequently, our model demonstrated its effectiveness by correctly classifying diseases in grape leaves.

Our model has a superior efficiency compared to the ensemble-learning-based models such as random forest (74.79%) (Jaisakthi et al., 2019) and AdaBoost (83%) (Jaisakthi et al., 2019). The accuracy of our model is also higher than the previous deep learning models such as deep convolutional neural network (DCNN) (88.70%) (Monowar et al. 2022), residual network (ResNet-18) (94.95%) (He et al., 2022), Alex network (AlexNet) (97.50%) (Wagle and Harikrishnan, 2021), hybrid convolutional neural network (Hy-CNN) (97.00%) (Kaur et al.), and visual geometry group network (VGGNet-19) (95.75%) (Kaur and Sharma, 2022). As a result, the efficiency of the proposed model was confirmed by comparison of the results of previous studies that used the same dataset for grape plant disease classification.

Table 3. Comparison of our model with the previous models on the same grape leaf dataset

Reference	Year	Method	Accuracy (%)
Nagi and Tripathy	2023	Fuzzy Probabilistic Neural Network	95.85
Kaur et al.	2022	Hybrid Convolutional Neural Network (Hy-CNN)	97.00
Monowar et al.	2022	Bootstrap Your Own Latent (BYOL)	88.90
		Simple Siamese (SimSiam)	87.30
		Cross Iterative Kernel K-means enhanced with Image Classification and Similarity Measurements (CIKICS)	85.70
		Deep Convolutional Neural Network (DCNN)	88.70
He et al.	2022	Residual Network (ResNet-18)	94.95
		Disease Image Recognition based on Bilinear Residual Networks (DIR-BiRN)	95.03
Joshi et al.	2022	Random Forest	95.00
Kaur and Sharma	2022	Visual Geometry Group Network (VGGNet-19)	95.75
Suo et al.	2022	Coordinated Attention Shuffle Mechanism Asymmetric Multi-scale Fusion Module Network (CASM-AMFMNet)	95.95
		Convolution and Self-Attention Network (CoAtNet)	88.74
Kurmi and Gangwar	2021	Bag-of-visual-words (BoW) + Fisher Vectors (FV) + Hand-Crafted Feature (HCF) + Support Vector Machine (SVM)	93.70
		BoW + FV + HCF + Logistic Regression	89.70
		BoW + FV + HCF + Multi-Layer Perceptron	92.80

Table 3. (continue)

Wagle and Harikrishnan	2021	Support Vector Machines	88.88
		Alex Network (AlexNet)	97.50
Ahil et al.	2021	Convolutional Neural Network	95.66
Ghosh and Roy	2021	Convolutional Neural Network	91.96
Thenmozhi et al.	2021	Feed-Forward Back Propagation - Neural Network	91.62
Jeyalakshmi and Radha	2020	Naive Bayes	81.87
		K-Nearest Neighbors	93.10
		Support Vector Machines	96.02
Jaisakthi et al.	2019	Support Vector Machines	93.04
		AdaBoost	83.00
		Random Forest	74.79
Adeel et al.	2019	Ensemble Subspace Discriminative (ESD)	93.70
		Cubic Support Vector Machine	93.60
		Quadratic Support Vector Machine	93.70
		Cosine K-Nearest Neighbors	90.00
		Multi-Class Support Vector Machines	94.10
Swetha and Jayaram	2019	Random Forest	86.00
		Support Vector Machines	84.00
		Decision Tree	78.00
		K-Nearest Neighbors	83.00
		Linear Regression	70.00
		Naive Bayes	77.00
Kaur et al.	2019	Fractional-order Zernike Moments (FZM) + SVM	97.34
		Scale-Invariant Feature Transform (SIFT) + SVM	87.44
		Speed Up Robust Feature (SURF) + SVM	88.01
		Histogram of Oriented Gradient (HOG) + SVM	89.54
		Zernike Moments (ZM) + SVM	91.33
Tarannum et al.	2017	Support Vector Machines	94.00
		average	*89.84*
Proposed model		**Convolutional Neural Network**	**98.53**

Besides the accuracy results, performance metrics such as precision, recall, and f-score values were compared to evaluate the proposed model's success in prediction. Jeyalakshmi and Radha (2020) obtained the results of approximately 0.9606 for all these metrics with the SVM method which achieved the highest accuracy in their study. He et al. (2022) achieved 0.959598 for recall, 0.958215 for precision, and 0.958533 for the f-score metrics with the Disease Image Recognition based on Bilinear Residual Networks (DIR-BiRN). Suo et al. (2022) reported that the CASM-AMFMNet resulted in values of 0.9600, 0.9592, and 0.9578 for precision, recall, and f-score performance values, respectively. Our proposed model achieved higher performance compared to the studies mentioned above with 0.985538, 0.985251, and 0.985226 for precision, recall, and f-score measurements, respectively.

5. CONCLUSION AND FUTURE WORK

Plant disease classification is an important research topic in machine learning since the identification of plant symptoms at early stages is one of the essential agricultural activities to increase cultivation yield and crop quality. The main focus of this study is the use of deep learning techniques for determining the type of disease from the input leaf images of the plants. It proposes a new convolutional neural network model that correctly classifies three types of grape plant diseases: isariopsis leaf spot, esca, and black rot. A web application was also implemented to help the farmers or people who plant for hobbies. The experiments carried out on real-world images showed that a significant improvement (8.7%) on average was achieved by the proposed CNN model (98.53%) compared to the previous models (89.84%) in terms of accuracy. Future studies could focus on adapting the CNN model for other kinds of plants such as potatoes and tomatoes.

CONFLICT OF INTEREST

The authors confirm that there is not any conflict of interest or common interest with any institution/organization or person.

AUTHORS CONTRIBUTION

Cemal Ihsan Sofuoglu: Determining the conceptual and design processes, Data collection, Data analysis and interpretation, Writing the original draft.

Derya Birant: Managing the conceptual and design processes, Reviewing, Editing, and Supervision.

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