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Disease Detection In Grapes Using CNN

Mahesh A Mali[1], Bhakti P Jadhav [2], Kabir G Kharade [3]
Department of Computer Science,Shivaji University, Kolhapur[1,2]
Assistant Professor, Department of Computer Science,Shivaji University, Kolhapur[3]
malimahesh399@gmail.com[1], bhakti1177@gmail.com[2] ,kgk_csd@unishivaji.ac.in[3]

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Abstract

In this research, Grape diseases significantly impact on production and fruit quality, leading to economical loss in agriculture sector. Traditional methods of disease detection is manually inspection which is time consuming and labor intensive with human errors to address this challenges. This study examine the application of Convolutional Neural Network (CNN) for automatic grape disease detection. CNN shows outstanding performance in image classification task, making them well suited for analyzing grape leaf images to identify diseases such as Black rot, Esca (Black Measles), and Leaf blight. This model trained on dataset comprising disease leaf and healthy grape leaf images, employing deep learning techniques for feature extraction and classification. Predicted result indicate that the CNN based approach achieves high accuracy in disease detection, offering a reliable, automated, and scalable solution for early detection. These research precision agriculture by facilitating immediate help and reduce chemical treatments, ultimately promote sustainable agriculture practices.

Introduction

Grapes is the one of the most cultivated fruits in the word it is mainly source for wine, fresh fruit, and fruits juice and raisins. Grape is typically caused by fungal, bacterial, and viral disease that affect to grape quality, Early disease detection is important for disease management and crop loss minimize, and avoid to excessive use of pesticide. Traditional disease detection method are human visual inspection, which can be unskillful and not effective for large vineyards. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have appeared as promising contenders for computer-based disease detection with the developments in computer vision and artificial intelligence. CNNs can learn hierarchical features from image data to classify grape leaf diseases precisely based on visual information. The goal of this study is to develop a CNN-based model for grape disease identification using image processing techniques. The key objectives are to establish a robust dataset, develop an optimal CNN structure, and benchmark its performance with traditional approaches. The desired method purpose is to enhance agricultural decision-making through the provision of an accurate, real-time diagnostic system, ultimately enhancing sustainable vineyard management and increasing crop yields.

Review Of Literature

A Diana Andrushila et al., presents an effective machine learning approach for early grape leaf disease detection using CNNC and IKNN models, achieving high classification accuracy (98.07%

for IKNN). The methodology is well-structured, leveraging histogram gradient-based features for improved classification. While the results outperform traditional models, the study lacks real-world testing and dataset diversity, limiting its generalization. Future work should focus on field validation and computational efficiency to enhance practical applications[1]. S.M. Jaisakthi et al.,proposes an automated system for grape leaf disease detection using image processing and machine learning. It employs GrabCut segmentation, feature extraction (GLCM for texture analysis), and classification using SVM, Random Forest, and AdaBoost. The SVM classifier with global thresholding achieved 93.03% accuracy, outperforming other models. While the approach is effective, real-world validation and dataset diversity are needed for practical applications[4].Sanjeev S Sannakki1 et al., presents an image processing-based approach for diagnosing grape leaf diseases using K-means clustering and Feedforward Backpropagation Neural Networks (BPNN). The system effectively segments diseased areas and extracts texture features using Gray Level Co-occurrence Matrix (GLCM). The proposed model achieved high classification accuracy, demonstrating its effectiveness for automated plant disease detection. However, testing on a larger dataset with diverse conditions could improve real-world applicability[5]. P. V. Yashvant et al.,proposes a Residual Skip Network-Based Super-Resolution Model (RSNSR-LDD) to enhance low-resolution grape leaf images for improved disease detection. By employing guided filtering and a deep learning-based classification network (DDN), the model achieves high accuracy (99.37%) on the PlantVillage dataset. The approach effectively handles poor-quality images but requires real-world validation for broader agricultural use[2].RajinderKumar M. Math1et al., presents a deep convolutional neural network (DCNN) model for early detection and classification of grape leaf diseases using RGB images from the PlantVillage dataset. The proposed model, developed from scratch, achieves 99.34% accuracy, outperforming some pre-trained models. It also highlights precision agriculture applications by enabling mobile device deployment using TensorFlow Lite. However, real-world validation with field-collected images is needed for broader applicability[3].zuhang hang1 et al., presents a machine learning-based approach for grape leaf disease detection using transfer learning techniques applied to VGG16, MobileNet, and AlexNet models. It classifies diseases like black rot, black measles, leaf blight, and phylloxera, achieving high accuracy, with an ensemble model reaching 100% accuracy. The study effectively reduces training time and enhances classification performance, but real-world testing on diverse datasets is needed for broader applicability[7]. Snekofa Ghoury et al., presents a real-time grape disease detection system using deep learning models Faster R-CNN Inception v2 and SSD MobileNet v1. The Faster R-CNN model achieved 95.57% accuracy but had a longer processing time (25-30 seconds per image), while SSD MobileNet v1 performed faster but with lower accuracy (59.29%). The study demonstrates the potential of Faster R-CNN for real-time disease detection, though improvements in speed and dataset diversity are needed for practical deployment [6].

Fig 1: Prediction Process Flowchart

Fig 1 Show the process starts with loading a trained AI model learn how to identify various categories. Upload an image,preprocessing to resize and change its format so model can examine it perfectly. The AI model analyze the image, compare it with the data. After comparing shows index with significant class name, for example disease name. After the appropriate name is recognized, the system predict the result.

PROPOSED METHODOLOGY

1. Data Collection & Preprocessing

•Dataset Preparation:

The data set comprises segmented images of leafy crops of various disease types.

•Loading Data:

Training and validation sets are loaded with keras. The images are resized to 128x128 pixels for uniformity.

•Batch Processing

The data is divided into batches of 32 images per batch for sufficient training. Images are shuffled so that model bias is avoided.

2. Model Development

CNN Architecture:A Convolutional Neural Network (CNN) is constructed using the TensorFlow model's Sequential mode.

•Used Layers:

•Convolutional Layers: Derive features from input images.

• MaxPooling Layers:Downsample spatial dimensions maintaining significant features.

• Dropout Layers: Prevent overfitting by dropping neurons at random during training.

• Flatten Layer: Maps feature maps to a one-dimensional vector.

• Fully Connected (Dense) Layers: Make predictions on the basis of extracted features.

• Softmax Activation: Used in the output layer to classify the images into 4 different diseases.

3. Model Compilation & Training

The model is then trained using the model.fit() function for 10 epochs.

Validation set is used to track model performance.

Training history is saved for visualization.

4. Model Performance & Evaluation

Accuracy Visualization:

Training and validation accuracies are plotted with Matplotlib to observe model learning trends.

•Confusion Matrix:

The predictions from the model are compared with actual labels to analyze classification errors. Seaborn heatmap is used to visualize the confusion matrix.

•Classification Report:

We use Scikit-Learn classification_report for the reporting of precision, recall, and F1-score of every class of disease.

5. Image Testing & Prediction

•Loading the Trained Model:

The model is loaded with keras.

•Image Preprocessing

Test images are resized to 128x128 pixels, and converted to an array that is expanded to match input sizes.

•Prediction Process:

The model makes the disease category prediction using model.predict().

•Result Visualization:

The test image is plotted with the expected disease name using Matplotlib.

```
Training_history = model.fit(
    x=Training_set,
    validation_data=Validation_set,
    epochs=10)
```

```
Epoch 1/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 627s 3s/step - accuracy: 0.5959 - loss: 1.0123 - val_accuracy: 0.8661 - val_loss: 0.3264
Epoch 2/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 632s 3s/step - accuracy: 0.8718 - loss: 0.3155 - val_accuracy: 0.9104 - val_loss: 0.2432
Epoch 3/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 661s 3s/step - accuracy: 0.9317 - loss: 0.1905 - val_accuracy: 0.9436 - val_loss: 0.1404
Epoch 4/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 657s 3s/step - accuracy: 0.9361 - loss: 0.1736 - val_accuracy: 0.9765 - val_loss: 0.0663
Epoch 5/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 681s 3s/step - accuracy: 0.9706 - loss: 0.0842 - val_accuracy: 0.9709 - val_loss: 0.0827
Epoch 6/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 651s 3s/step - accuracy: 0.9812 - loss: 0.0600 - val_accuracy: 0.9868 - val_loss: 0.0427
Epoch 7/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 657s 3s/step - accuracy: 0.9806 - loss: 0.0522 - val_accuracy: 0.9298 - val_loss: 0.2021
Epoch 8/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 653s 3s/step - accuracy: 0.9807 - loss: 0.0540 - val_accuracy: 0.9940 - val_loss: 0.0206
Epoch 9/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 380s 2s/step - accuracy: 0.9794 - loss: 0.0558 - val_accuracy: 0.9918 - val_loss: 0.0219
Epoch 10/10
226/226 ━━━━━━━━━━━━━━━━━━━━ 366s 2s/step - accuracy: 0.9909 - loss: 0.0256 - val_accuracy: 0.9989 - val_loss: 0.0040
```

Fig. 2: Training of dataset

Fig 2: shows the training of a deep learning model with tensorflow. This model is trained 10 epochs, and accuracy and loss of training set and validation set, both increase over time. The training accuracy goes from 59.59% to 99.99% and validation accuracy also increasesand showing good performance. The loss value go down, indicating that the model is learning well.

```
train_loss,train_acc = model.evaluate(Training_set)
```

```
226/226 ━━━━━━━━━━━━━━━━━━━━ 82s 361ms/step - accuracy: 0.9978 - loss: 0.0053
```

Model Evolution On Training Set

```
print(train_acc,train_loss)
```

```
0.9988922476768494 0.004018537700176239
```

```
#Model on validation set
val_loss,val_acc = model.evaluate(Validation_set)
```

```
226/226 ━━━━━━━━━━━━━━━━━━━━ 81s 359ms/step - accuracy: 0.9990 - loss: 0.0038
```

```
print (val_acc,val_loss)
```

```
0.9988922476768494 0.004018538165837526
```

Fig.3: Accuracy calculation using CNN model

This fig shows the result of trained deep learning models evalution on training and validation sets. The model shows almost 99.98% accuracy with loss, shows outstanding performance.

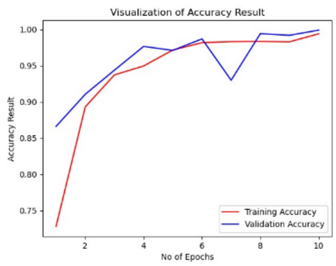

Fig.4 Comparative chart to display accuracy using training and validation data

Fig. 4 shows the graph visualize the accuracy of deep learning model over 10 epochs for both training and validation data. Both accuracy improves over time.

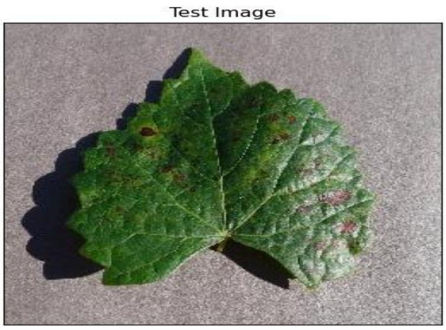

Fig.5: Affected grape leaf used during the process

Fig. 5 shows an image of grape leaf used to analysis process.

Fig.6: result showcasing affected leaf, impacted with Black Measles disease

Fig.6 shows the predicted result, identify the leaf as affected by "Black Measles" disease. This demonstrate the system ability to detect and classify grape leaf disease accurately.

Conclusion

This paper suggests an effective machine learning-based approach to Grape disease detection using a Convolutional Neural Network (CNN). The model was trained on a sample set of Grape leaf image data labeled into 4 classes of diseases. Through a number of convolutional and max-pooling layers, the model can capture spatial features and classify grape disease with decent accuracy. The training converged stably, with the validation accuracy closely following the training accuracy, showing minimal overfitting. Performance measurement through a confusion matrix and classification report verified the model to be able to generalize well across a variety of disease classes. The final trained model was successfully deployed for real-time classification of disease on leaf images. This paper illustrates the capability of machine learning for automated grape disease detection and offers a scalable and fast solution for agricultural disease diagnosis. Future enhancements may include the use of transfer learning, data augmentation techniques, and real-world field testing for enhanced accuracy and robustness improvements.

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