GRAPES LEAF DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK

BY

Md. Aktaruzzaman

ID: 213-25-048

This report is presented in partial compliance with the Requirements for the Degree of Master of Science in Computer Science and Engineering.

Supervised By

Mr. Abdus Sattar
Assistant Professor & Coordinator M. Sc
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Thesis titled **"Grapes Leaf Disease Detection using Convolutional Neural Network"**, submitted by Md. Aktaruzzaman, ID No. 213-25-048 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **11-01-2025**

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We hereby declare that this thesis has been done by us under the watchful eye of **Mr. Abdus Sattar, Assistant Professor & Coordinator M. Sc, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Mr. Abdus Sattar
Assistant Professor & Coordinator M.Sc
Department of CSE
Daffodil International University

Submitted by:

Md. Aktaruzzaman
ID: 213-25-048
Department of CSE
Daffodil International University

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ABSTRACT

Grapes a well-known flavourful, bulb-shaped fruits, also called botanically Vitis vinifera. The pulp appears inside its juicy and sweet taste with few pips or seeds. Despite being the world's most generated fruit, grapes productivity has become less due to Its leaf disease. Because of viruses, bacteria, and fungi, it mainly occurs and reduces the proper growth of fruit. The disease primarily attacks the leaf and damages the full grapes plant. So, it is necessary to detect grape leaf disease. A proper diagnosis minimizes the presence of leaf disease. In order to detect grapes leaf disease, we applied the Convolutional Neural Network, a leading deep learning model. It is the major part of our proposed research work. CNN takes part as a good image processing technique. We divided the dataset both for training and testing purposes. The entire research work shows that the proposed model can effectively identify grape leaf disease appropriately. Here, the experimental outcome successfully gives a 98% accuracy rate.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Grapes are grown in clusters. It is a familiar fruit which is used to produce juice. The refreshing fruits are certainly a good source of minerals and its juice is mild lenitive. It originates both from Western Asia and Europe. The most grape manufacturing states are Maharashtra and Karnataka. Arie et al. [1], in their paper recommended grapes have healing power; hence they can cure various diseases. The fruit removes the lack of nutrition and works as a remedy for different health problems. Harvesting grapes is cost-effective. But the growing existence of grape leaf disease is injurious to our farmers. Because of leaf disease, the fruit is producing little, and a large number of grapes are damaged. These diseases hinder the thriving of grapes. To save the fruit, it needs to describe the disease beforehand. The proposed CNN model detects grape leaf disease adeptly. The model has expansive knowledge of disease detection. Tanmay et al. [2], focused primarily on four grapevine diseases the things that cause disastrous crop losses all the year-round. Zinon et al. [3], proposed to improve product quality, handle costs, and decrease losses early detection of grapes disease is necessary. Our method is efficient in diminishing the leaf diseases including Black Rot, ESCA, Healthy, and Leaf Blight which indicates massive loss. This work has three major sections such as (i) literature review: the field gives a review of some related works, (ii) research methodology: which illustrates the details of the proposed approach, (iii) experimental results and discussion: particularly representing the experiment with their details and displays the outcome. The approach assures the necessity of leaf disease detection. By applying CNN, the method provides as well accurate results.

1.2 Motivation

The motivation behind the research is farmers face strong challenges in detecting grape leaf disease. Traditional disease detection methods like manual inspection are very time-consuming, labor intensive, and sometimes seem incorrect. The advancement of machine learning, particularly Convolutional Neural Network (CNN) gives the automatic and progressive detection process. CNN provides a more precise and efficient pathway for early disease detection and intervention that is easy for reducing crop loss.

1.3 Objectives

To develop a robust model that uses a Convolutional Neural Network (CNN) to detect grapes leaf from images.

To generate a dataset from grape leaf images, including healthy and diseased samples, for training and evaluation of the CNN model.

To estimate the performance of accuracy, precision, recall, and other relevant metrics by using the CNN model.

To identify the crucial diseases affecting grape leaf that the model should be able to detect.

To emplace the model giving farmers a tool for reliable disease detection.

1.4 Research Questions

- Can CNN-based models perform traditional disease detection systems for the accuracy of grape leaves?
- How does dataset quality influence CNN performance in detecting grape leaf diseases?

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The section sets the stage by presenting the problem and outlining its significance. Machine Learning, particularly Convolutional Neural Network(CNN) has demonstrated significant success in image classification tasks. Utilizing CNNs to detect various grapes leaf diseases, providing a reliable, scalable, and efficient solution. Through the medium of training a deep learning model of grapes leaf images, this method could aid farmers and agricultural specialists in detecting disease in advance, leading to better crop management and abated pesticide use.

2.2 Literature Review

There are Some earlier experiments have reviewed in this portion. It has been noted that much research work has been done on leaf disease detection using Convolutional Neural Network. To determine grapes leaf disease researchers have been able to accomplish their goals. Consequently, through the Convolutional Neural Network, it has acquired a sensible accuracy rate.

In the study [4], where Xiaoyue et al. worked for identifying leaf disease of grapes a detector has used DR-IACNN based on deep learning. An augmented dataset of 62,286 diseased images of the leaf was formed. The system was able to obtain 81.1% accuracy from the collected dataset.

Jaisakthi et al. [5] presented a paper on an automatic segmentation approach called the grab-cutting approach which segments the leaf from the image background. There are some machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and AdaBoost algorithm have been used in the research work. Used 5675 grapes leaf disease dataset and the classification result is 93%.

Pranjali et al. [6] recommended SVM classification techniques, First of all, segmentation is used via K-means clustering, after that two features are extracted named color and texture. The obtained accuracy is 88.89%.

Prathamesh et al. [7] presented a paper on processed grape leaf images. After that, they have utilized the Kohonen classifier. The obtained outcome is 93.44%.

Bhavya et al. [8] presented a paper on the Transfer Learning model which is used to detect grapes leaf disease. A confusion matrix is also used. The dataset contains works in different classes. The attained accuracy is 91.66%.

Heena et al. [9] used the CNN model and Random Forest algorithm to identify citrus leaf disease. The achieved accuracy is 87%.

Khan et al. [10] have taken an M-class SVM used for classification. The obtained result is based on color features, CCA, and NCA approach. The final classification accuracy is 94.1%.

2.3 Scope of the Problem

The scope of the problem defines the extent of the research and the specific focus within the broader area. The scope of this research focuses on the following aspects:

Disease Types: Focusing on the detection of general grape leaf diseases, such as Black Rot, ESCA, Healthy, and Leaf Blight among others.
Image-Based Detection: The research will utilize images of grape leaves as the primary input data.
Convolutional Neural Network: The study will use Convolutional Neural network(CNN) which has proven to be effective in image recognition tasks. The proposed method will involve developing, training, and evaluating CNN architectures tailored for grape leaf disease detection.
Dataset: Both healthy leaves and various disease-affected leaves will be used to train and test the CNN model to ensure that the model learns to distinguish between diverse conditions.
Evaluation Metrics: The model's performance will be assessed using common evaluation metrics including accuracy, precision, recall, and F1-score. They will be used to measure how well the CNN can classify images of healthy and diseased leaves.

2.4 Challenges

This section discusses the existing research in the field and the challenges faced by previous works. It highlights the gaps in current methods, motivating the need for the proposed solution. For grapes leaf disease detection, the following challenges are:

Data Availability and Quality: Many existing studies suffer from limited datasets of grape leaves or poor image quality. High-quality, labeled datasets are essential for training deep learning models effectively. Often, publicly available datasets are either too small or lack diversity in terms of disease types and environmental conditions.

Generalization of Models: Many existing models perform well on specific datasets but fail to generalize to new, unseen data. The variations in lighting conditions, angles, and leaf appearance across different regions. These can hinder the model's ability to detect diseases accurately in diverse conditions.

Overfitting: Deep learning models, including CNNs, are susceptible to overfitting, especially when the dataset is small or not sufficiently diverse. Overfitting happens when the model learns the details and noise in the training data to the extent that it negatively impacts its performance on unseen data.

Complexity and Computation: Training CNN models can be computationally expensive and time-consuming, requiring high-performance hardware and substantial computational resources. This can limit the practical implementation of disease detection systems in resource-constrained environments.

Imbalance in Data: Many disease classification tasks suffer from imbalanced datasets, where certain classes (e.g., healthy leaves) dominate, while others (e.g., diseased leaves) are underrepresented. This imbalance can lead to biased models, where the model may tend to predict healthy leaves more accurately than diseased ones.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Block Diagram of the Proposed Model

The model is wielded to detect grapes leaf disease. To pick a disease, the proposed method is more valuable. Four different classes of samples were taken with achieving accuracy is 98%. Each leaf disease is divided into various numbers of images. The model illustrates some important phases. It explains the details analysis of methodology. The phases are as follows:

a) Input image dataset
b) Preprocessing
c) Feature Extraction
d) Train and Test data

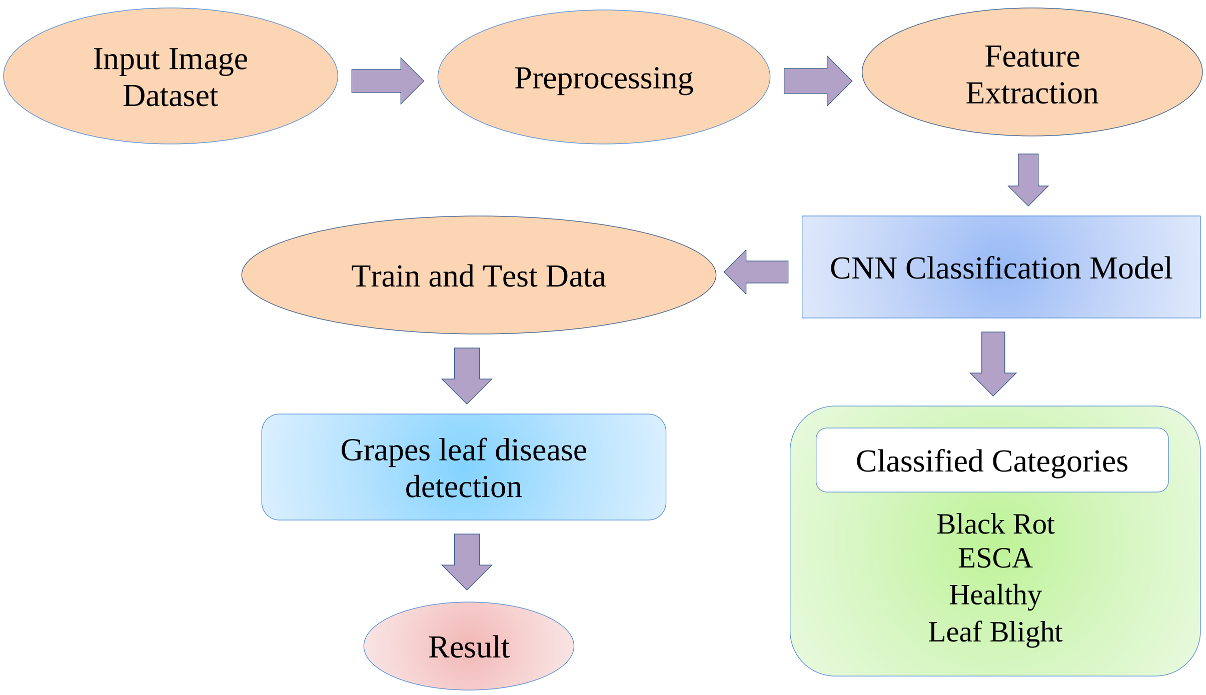

Figure 3.1: Block Diagram of the Proposed Model

3.2 Input Image Dataset

A dataset defines a set of collected data for a particular problem. Every dataset is dissimilar from another dataset. Sometimes, it may have changed. Then Xlsx or HTML format is used. We have taken the dataset from the Kaggle platform.

Figure 3.2: Sample images of the collected dataset

3.3 Preprocessing

To get proper results Preprocessing is utilized. It transforms the raw data into both clean and suitable datasets. It impacts heavily on image quality. If the image is not clear, the process can not perform properly. It increases the accuracy and efficiency of a model. Numerous dimensions of the image are taken as sample images which are divided into assorted images. The Convolutional Neural Network (CNN) model uses a 224*224 pixel image as input because of standardization, feature extraction, aspect ratio, etc. It originally made a balance between image resolution and similarity among the existing model and datasets. An important step normalization is used to get the pixel values of images. A well-known filter named Gaussian is operated for smoothing images. Images have transformed into grayscale. Another crucial step is to label all the images. Finally, both the training and testing dataset have pointed out four classes.

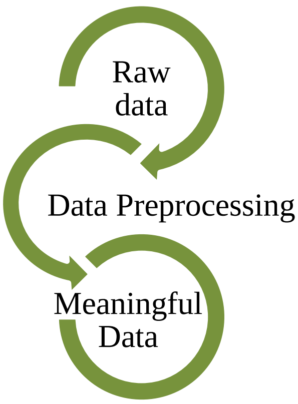

Figure 3.3: Data Preprocessing

3.4 Feature Extraction

The process is used to make complicated information easier. It reduces data complexity. Sometimes, it works on new feature creation. A list of features including color features, shape features, and texture features is applied in the method. Based on their functionality, all the features are particularly worked. The feature extraction process is applied for classification. It makes the dataset easier and increases the accuracy to the upper level.

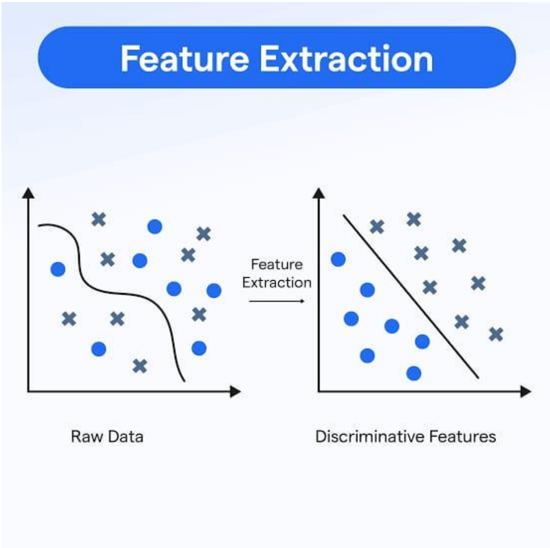

Figure 3.4: Feature Extraction

3.5 Train and Test Data

We trained the datasets using grapes leaf diseases. We implemented by Convolutional Neural Network algorithm for training based on the provided dataset.

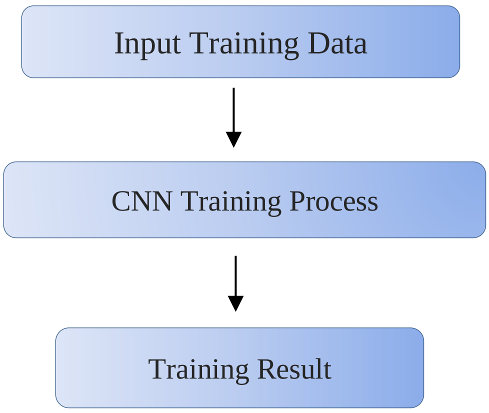

Figure 3.5: Training Phase of the Model

We have tested our data after completing the training part. We use 409 epoch size both for training and testing purposes.

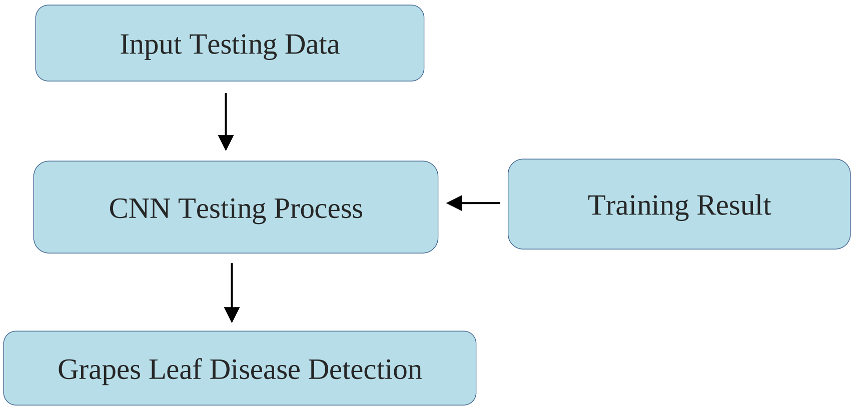

Figure 3.6: Testing Phase of the Model

3.6 CNN Model

Convolutional Neural Network (CNN) Convolutional Neural Network, is extensively known as ConvNet. It is a deep-learning algorithm that performs object detection. This model learns features using filter (or kernel) optimization. CNN is mainly a powerful tool. It needs to be trained with a high-power processor like GPU. CNNs applied image data. The image contains pixel values. It uses three-dimensional data with colored images named RGB (Red, Green, Blue). Finally, the image creates a 3-dimensional structure which is known as input volume (255*255*3). CNN Algorithm detects disease from infected grape leaf images along with providing accurate results.

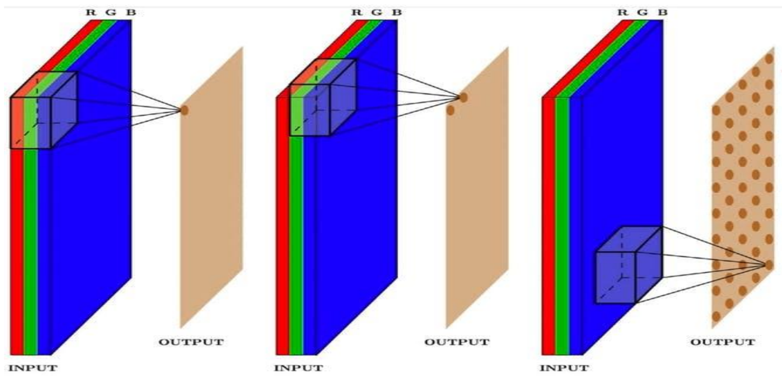

Figure 3.7: Structure of CNN Model

3.6.1 CNN Model Steps

a) Conv2D: These steps convolve the image into multiple images
b) Flatten: Used to flatten the dimensions of the image
c) Image Data Generator: To rescale the image it has used
d) Training Process: Used to prepare test data
e) Epochs: Tells the number of times the model which used for training both forward and backward passes.
f) Validation process: Used to feed the validation/test data into the model. This step denotes the number of test samples.

3.6.2 Architecture of CNN Model

3.6.2.1 ResNet-50:

A deep convolutional neural network(CNN) armature named ResNet-50 was developed by Microsoft Research. The architecture stands for “Residual Network”. The number “50” indicates the layers displayed in the network. That is why, it is called ResNet-50. It is a strong image classification technique. The model is trained on a large amount of data. The model can gain state-of-the-art results from object detection.

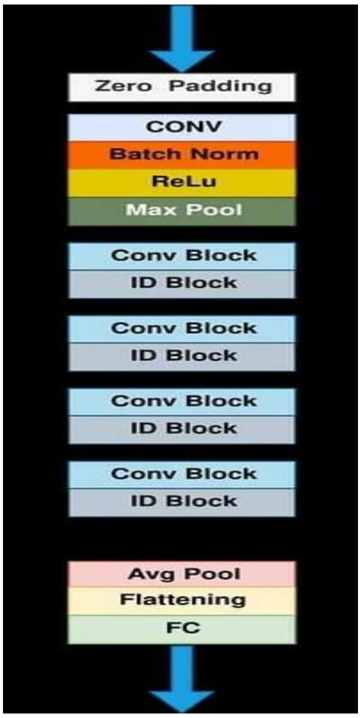

Figure 3.8: ResNet-50 Architecture

The main components of Resnet-50 are given below-

1) Convolutional Layer: The first layer which performs convolution. Convolution involves applying filters to input images. From the input image, the layers worked to extract features including shapes, textures, and edges.
2) Residual Block: The layer consists of two convolutional layers that follow both batch normalization and ReLu function. It passes the input and attaches the input back to the output.
3) Fully Connected Layer: It is also called a dense layer. The number of output classes in the layer is the same as the number of Neurons.

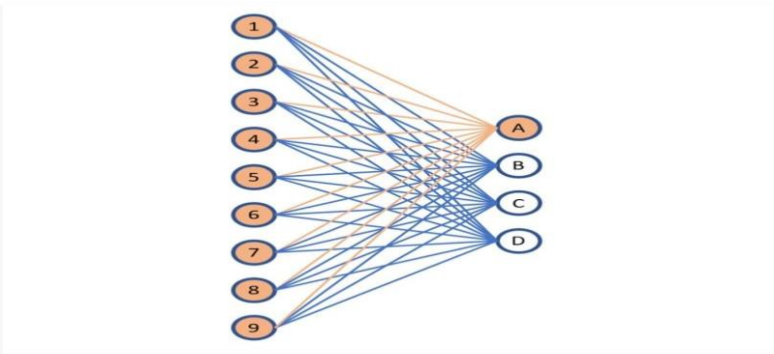

Figure 3.9 Fully Connected Layer

The key features of ResNet-50 are-

- Skip Connection: This connection is well known as an identity connection. It is implemented by adding a previous later output to a later layer output.

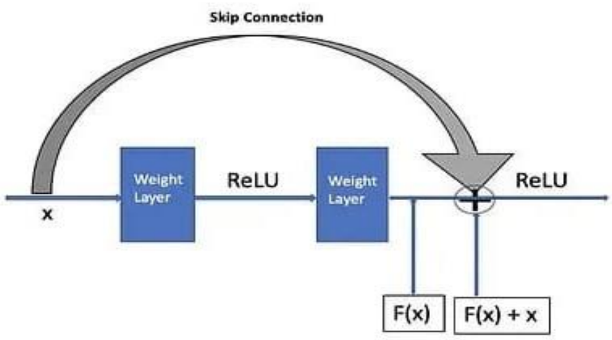

Figure 3.10: Skip Connection

3.6.2.2 EfficientNet

A traditional and powerful convolutional Neural Network architecture. EfficientNet uses a compound coefficient Φ. The whole size of the networks is displayed through the combination of depth scaling, width scaling, and resolution scaling.

$$\text{depth: } d = \alpha\Phi \text{ ………(i)}$$

$$\text{width: } w = \beta\Phi\text{………(ii)}$$

$$\text{resolution: } r = \gamma\Phi\text{………(iii)}$$

$$\text{s.t. } \alpha. \beta^2 . \gamma^2 \approx 2$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

Figure 3.11: Compound Scaling

Here,

α,β, γ are consonants

They denote through a little search that is called grid search.

ϕ (phi): A compound coefficient, a positive integer, that governs the overall scaling of the model.

This formula defines how the model's depth, width, and resolution should be scaled to achieve optimal performance.

EfficientNet Architecture: It utilizes Mobile Inverted Bottolnect (MBConV) layers. It also utilizes the Squeeze-and-Excitation (SE) optimization to increase the performance of the model.

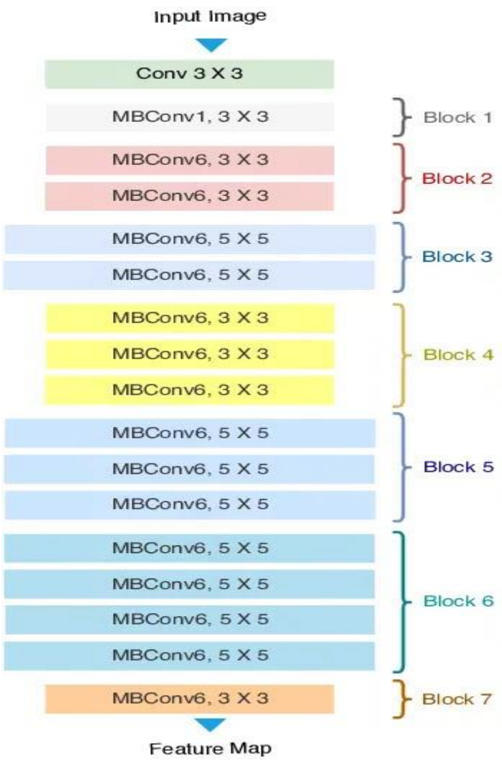

Figure 3.12 EfficientNet Architecture

EEfficientNet has separate variants like EfficientNet-B0, EfficientNet-B1 etc. The system makes a balance between accuracy and effectiveness.

Advantages of EfficientNet Architecture-

- Enables faster training
- Obtain state-of-the-art performance
- The scaling system allows for flexibility

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Dataset Description

The dataset refers to the collection of required data. Datasets may images, numeric values, or explanations of objects. The number of collected datasets is 3271 which has been taken from the Kaggle Platform of four different classes. They are (i) Black Rot, (ii) ESCA (Black_Measles), (iii) Healthy, and (iv) Leaf Blight (Isariopsis_Leaf_Spot).

Black Rot: It happens due to the fungus Gugnardia bidwellii. The disease attacks the leaf during humid weather and spreads among all the green portions including fruits and leaves.

ESCA: It reflects spots in both the leaf and fruit along with creating black existence.

Leaf Blight: Because of the fungus Helming thosporium turcicum pass, it happens. It reduces the proper growth of seedlings.

Table 1 displays image samples with their class labels-

Table 4.1 Example images with their corresponding class labels

Class label	Image sample
Black Rot	
ESCA(Black_Measles)	
Healthy	
Leaf Blight (Isariopsis_Leaf_Spot)	

The data is split into two portions, one is for the training set and another one is for the testing set. The Training dataset bears 80% including 2617 number of the leaf disease. The testing set bears 20% including 654 number of the collected dataset.

4.2 Experimental Setup

The procedure is accustomed to epitomize the gathered data. We implemented our experiment by using a Convolutional Neural Network (CNN).

The Hardware, Software and other necessary tools we used in our research experiment are-

Required System Hardware and Software:

- GPU
- Storage Disk
- Fast Internet Connection
- Frameworks for deep learning:
    a. Tensorflow framework
    b. Keras API for deep learning
    c. OpenCV (image processing library)

Libraries:

- Python programming language
- Numpy (Numerical Python)
- Matplotlib (Plotting library)
- Scikit-learn

Essential Tools:

- Google AI Platform: Kaggle
- Dataset: Sourced from the Kaggle platform
- Algorithm used: Convolutional Neural Network (CNN)

4.3 Confusion Matrix Results

We implemented a Convolutional Neural Network for our task. Finally, the obtained accuracy is 98%. The epoch number is 409. Through the operation of CNN, the confusion matrix is generated-

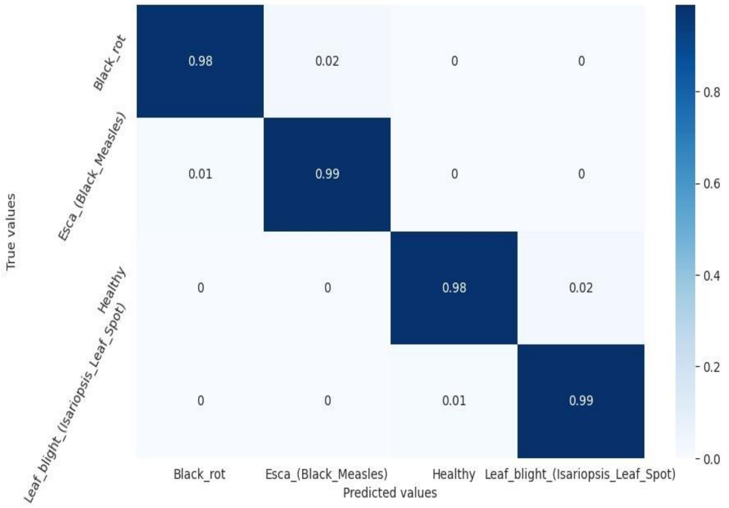

Figure 4.1: Confusion Matrix Results

Another accuracy matrix provides precision, recall, and f1 score in the model.

Precision: Exactly predicted positive performance observations. It defines true positive.

Recall: It represents true negative.

F1-score: It is a harmonious mean of both precision and recall. Based on precision and recall, it makes the same weightage.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = \frac{2 * P * R}{P + R} \quad (4)$$

Figure 4.2: Evaluation criteria for model performance

Table 2 displays the precision, recall, and f1-score of our task.

Table 4.2 Precision, recall, and f1-score of four classes

	precision	recall	f1-score
Black_rot	0.98	0.98	0.98
Esca_(Black_Measles)	0.99	0.99	0.99
Healthy	0.98	0.98	0.98
Leaf_blight_(Isariopsis_Leaf_Spot)	0.99	0.99	0.99

4.4 Model Accuracy

The matplotlib.pyplot library is used to visualize the results. The following figure shows the training performance of the CNN model.

Figure 4.3: Model Performance during Training

4.5 Model Loss

The figure expresses the testing performance of the CNN model-

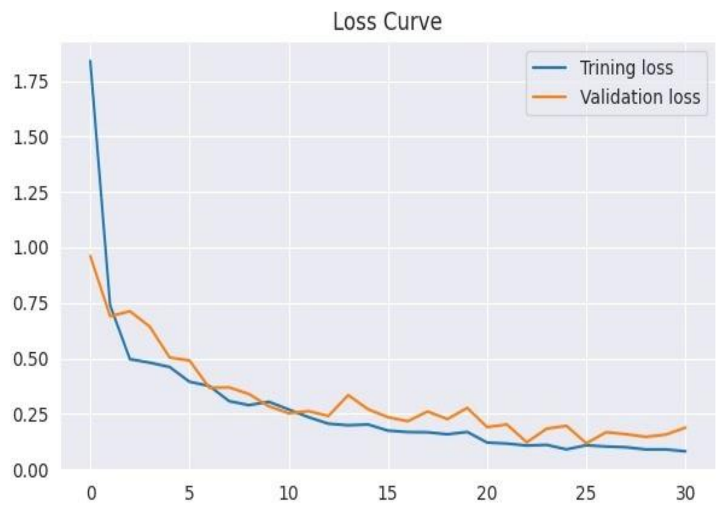

Figure 4.4: Model Performance during Testing

4.6 Comparative Study

This part represents the summary of the proposed model with other models.

Table 4.3 Summary of the proposed model and other model

Source Methodology	Objectives	Result
CNN	The study used a Convolutional Neural Network (CNN) for the detection of grape leaf diseases using image data.	The CNN model achieved high accuracy in detecting and classifying grape leaf diseases, showing promising performance in disease identification.
DR-ICANN	They have taken an augmented dataset to gain successful accuracy.	They have used DR-ICANN using a deep learning model to come to a fruitful conclusion point.

Support Vector Machine (SVM), Random Forest, AdaBoost	The system used grab cutting approach for the segmentation process.	Using Machine Learning algorithms, the research has got better accuracy.
SVM	They concentrated K-means clustering method for implementing segmentation.	This work has recommended a well-known SVM classification technique.
Transfer Learning	They used a confusion matrix.	Working with different classes, it used the Transfer Learning method.
CNN, Random Forest	The research study has used both the CNN model and the Random Forest algorithm to identify citrus leaf disease.	This work has achieved better accuracy through using CNN and Random Forest.

Another table shows us the comparative performance with other works.

Table 4.4 Comparison between the proposed model and other model

Reference	Approach	Research Field	Accuracy (%)
This work	CNN	Grapes Leaf Disease	98%
B.Jain, S. Periyasamy[8]	Transfer Learning	Grapes Leaf Disease	91.66%
P.B. Padol, A. A. Yadav[6]	SVM	Grapes Leaf Disease	88.89%
A.A, K.MA et all[10]	M-SVM	Grapes Leaf Disease	94.1%

4.7 Advantages

Advantages of the proposed system:

- Reduced complexity
- Appropriate classification

- Uncomplicated and easy to use
- Environment friendly
- High-level accuracy

4.8 Sample code screenshots:

```
# Compute confusion matrix
cm = confusion_matrix(y_test, pred,normalize="true")
cmm= np.around(cm.astype('float') / cm.sum(axis=1)[:, np.newaxis], decimals=2)
# Calculate the overall accuracy of the model
accuracy = np.trace(cmm) / float(np.sum(cmm))

# Define class labels
class_names = ["Black_rot","Esca_(Black_Measles)","Healthy","Leaf_blight_(Isariopsis_Leaf_Spot)"]

# Plot confusion matrix
plt.figure(figsize=(10, 6))
sns.heatmap(cmm, annot=True, cmap='Blues', fmt='g', xticklabels=class_names, yticklabels=class_names, annot_kws={"size": 10})
plt.xlabel('Predicted values')
plt.ylabel('True values')
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks + 0.5, class_names)#
plt.yticks(tick_marks + 0.5, class_names,rotation=60)
#plt.title('Confusion Matrix (Accuracy={:.2f}%)'.format(accuracy*100))
plt.savefig("/kaggle/working/Confusion.png",dpi = 300)

plt.show()
```

Figure 4.5 Sample code screenshots

4.9 Sample code screenshots:

```
24]:
from sklearn.metrics import confusion_matrix

# Calculate the confusion matrix
confusion_mat = confusion_matrix(y_test, pred)

# Print the confusion matrix
print("Confusion Matrix:")
print(confusion_mat)
```

```
Confusion Matrix:
[[115   2   0   0]
 [  2 137   0   0]
 [  0   0  43   1]
 [  0   0   1 108]]
```

Figure 4.6 Sample code screenshots

4.10 Sample code screenshots:

```
### loss curve ###

plt.figure(figsize=(7,4))
plt.plot(fin1['loss'], label='Trining loss')
plt.plot(fin1['val_loss'], label='Validation loss')

plt.title('Loss Curve')

plt.savefig("/kaggle/working/loss.png",dpi = 300)
plt.legend(loc='upper right')
```

Figure 4.7 Sample code screenshots

4.11 Sample code screenshots:

```
21]:
model.load_weights("/kaggle/working/skinCNNbest1claheIn.keras")
Adam = keras.optimizers.Adam(learning_rate=0.001)
preds = model.evaluate(test_gen)
print ("Loss = ",float(preds[0]))
print ("test Accuracy = ",float(preds[1])*100)
```

```
409/409 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9852 - loss: 0.0620
Loss =  0.06263507157564163
test Accuracy =  98.53300452232361
```

Figure 4.8 Sample code screenshots

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

a) **Increased Agricultural Productivity:** The earlier capableness of grape leaf disease detection helps the farmers to operate crops adequately. It reduces losses of the crop which ensues because of undetected disease. This gives rise to upper harvests and more continuous manufacturing along with profiting not only local but also global economies.

b) **Enhanced Food Security:** Grapes play a fundamental role in the food industry as they make wines along with numerous processed products. Food security is improved by early disease detection. This assures a wavering supply of quality grapes for eaters.

c) **Public Health and Healthcare Systems:** Too soon the disease detection signifies harmless chemicals are used to make less of pesticides. This benefits both human health and the environment by lowering disclosure to detrimental agrichemicals.

5.2 Ethical Aspects

a) **Data Security and Confidentiality:** In addition to grape leaf images, the CNN model requires access to extensive datasets. It is crucial to ensure that this data is collected ethically, with the informed consent of farmers, and that sensitive information is handled responsibly to prevent misuse.

b) **Access to Technological resources:** Some technology may be inaccessible for low-income areas farmers. The risk happens because CNN has the potential to transform agriculture. Assuring equitable access and uncreative a technology gap between large agribusiness and smallholders is an essential ethical consideration.

c) **Transparency in decision-making:** The decisions need to be transparent, especially if they influence large-scale agricultural decisions. It is important to understand for the farmers to understand how the model operates so that they can get clarifications or appeal decisions if necessary.

5.3 Sustainability Plan

a) **Sustainable Environmental Management:** The need for pesticide applications can be significantly decreased by early disease detection. Pesticides can have detrimental effects on the environment, such as soil degradation and water pollution. Early disease detection allows for more precise pesticide application, minimizing environmental harm and promoting more sustainable agricultural practices.

b) **Efficient Use of Resources:** CNN can help optimize the use of resources including fertilizers and water for efficient disease detection. This helps to make waste less and raise the whole farm management resources. It is particularly crucial in regions with limited resources, such as areas affected by drought.

c) **Sustainable Crop Health Over Time:** This disease detection system can help farmers implement more sustainable crop management approaches. These practices help maintain soil health and enhance grape leaf resilience over the long term, reducing the reliance on heavy agricultural inputs.

d) **Cooperation with Local Communities:** The sustainability of the research depends on cooperation with local farming communities. It ensures the model is tailored to specific grapevine varieties, local conditions, and common diseases across different regions. Promoting local involvement in data collection and model refinement will enhance sustainability and contribute to the technology's long-term success.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

The research focuses on grapes leaf disease detection using Convolutional Neural Network (CNN). CNN is a deep learning algorithm that is particularly effective at image recognition tasks. The study involves gathering a dataset of grape leaf image diseases such as Black Rot, ESCA, Healthy, and Leaf Blight. Then images are preprocessed and used to train a CNN model to detect leaf images into healthy or diseased categories. The goal of this research study is to enhance the accuracy and efficiency compared to traditional methods. It can be time-consuming and cause human error. CNN is particularly useful. Because the model can automatically identify relevant features from the images during training, it reduces the need for manual feature extraction.

6.2 Conclusion

The research displays that CNN is highly effective in detecting disease from grape leaf images. The proposed model illustrates a complementary solution readily. The model achieved high accuracy, showing its potential for use in real-world agricultural applications. The disease detection system enables farmers to identify problems early, allowing them to take prompt action such as applying pesticides or modifying environmental conditions, to reduce crop loss.

6.3 Implementation for Further Work

Enlarging the Dataset: Increasing the dataset with more diverse images from various environmental conditions will improve the model's robustness and ability to generalize. This expansion would also make the system applicable to a wider range of grapevine varieties and regions.

Classifying Multiple Diseases: While the current model focuses on a limited number of diseases, further research could enhance its ability to identify a broader spectrum of grape leaf diseases, thereby increasing its usefulness for farmers.

Incorporating Precision Agriculture Tools: The systems could be integrated with other precision agriculture tools, such as irrigation management or nutrient monitoring systems, to provide a comprehensive solution for vineyard management.

Enhancing Model Efficiency: Although CNNs are powerful, they can be computationally intensive. Future developments could optimize the model to run efficiently on lower-powered devices, making it more practical for real-time, on-site use.

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