GRAPE LEAFS DISEASE DETECTION USING CUSTOMIZED CNN MODEL

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"GRAPE LEAFS DISEASE DETECTION USING CUSTOMIZED CNN MODEL"**, submitted by **NAZMUS SAKIB** 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 B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15/07/2024.

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DECLARATION

I hereby declare that this project has been done by me under the supervision of **Mr. Saiful Islam, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This study looks at the diagnosis of grape leaf illnesses using a Kaggle dataset that is categorized into four categories: "esca," "black rot," "healthy," and "leaf blight." The study introduces a brand-new illness categorization method based on Convolutional Neural Networks (CNN) models. For comparison, the popular pre-trained models MobileNet and VGG16 are also used. The primary goal is to offer a reliable and effective technique for the automated identification and categorization of diseases affecting grape leaves, an essential task for the timely diagnosis and medical care of illnesses in the wine industry.

Preprocessing methods, such as data augmentation and normalization, are used in the study to improve model performance. Experimental assessments are performed on the dataset to compare the proposed CNN model with MobileNet and VGG16 in terms of accuracy, precision, recall, and F1-score. The modified CNN model is effective at correctly recognizing grape leaf diseases, according to the results. In summary, this thesis advances automated disease identification in viticulture by shedding light on which CNN architectures are most suited for a given job and laying the groundwork for future studies in agricultural image processing.

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VGG16 [Visual Geometry Group]

MOBILENET [Computer vision model]

CUSTOMIZED CNN [Convolutional Neural Network]

CHAPTER 1
INTRODUCTION

1.1 Introduction

Grapevine illnesses are a major issue for the wine industry, affecting grape quality and abdicate universally. Avoiding these illnesses and keeping vineyards solid are basic to guaranteeing long-term grape generation. Utilizing computer vision and machine learning methods, computerized illness recognizable proof has developed as a promising procedure to viably fathom these challenges among other strategies. Large-scale datasets like those from Kaggle have made research on grape leaf disease identification easier.These databases frequently contain images of grape leaves with a variety of diseases, including leaf blight, esca, black rot, and healthy leaves. Scientists have developed machine learning models that accurately diagnose and classify grapevine diseases using these datasets. The essential center of this proposition is the advancement and assessment of a novel strategy for grape leaf infection distinguishing proof. By displaying a Convolutional Neural Organize (CNN) show particularly custom fitted for the classification of grapevine illnesses, our work points to create a critical commitment to the field. We also present a performance comparison between our customized CNN model and two popular pre-trained models, MobileNet and VGG16. The rationale behind using MobileNet and VGG16 for comparison is their widespread use and demonstrated effectiveness in image classification applications. We aim to establish the efficacy of our customized CNN model in correctly identifying and classifying grape leaf illnesses by comparing it to various benchmark models. Additionally, this study sheds light on the applicability of various CNN designs for the detection of grapevine disease, which may influence future agricultural image processing research efforts. In conclusion, this thesis develops and assesses machine learning models to answer the urgent demand for automated grape leaf disease detection. We hope to improve viticulture management practices and open the door to more effective disease identification and management in vineyards by utilizing cutting-edge methods and contrasting various structures.

1.2 Motivation

The substantial financial impact that grapevine diseases have on viticulture is the driving force for this research. Diseases that affect grapevines can result in significant yield and quality losses, endangering the wine industry's viability as well as the livelihoods of grape producers. To reduce their negative effects and conduct prompt therapies, early diagnosis of these disorders is essential. Expert visual inspection is a common component of traditional disease diagnostic techniques, although it can be laborious, subjective, and error-prone.

The emergence of computer vision and machine learning techniques offers a promising alternative for automated disease detection in vineyards. By harnessing the power of artificial intelligence, we can develop systems capable of accurately and efficiently identifying grapevine diseases based on leaf images. This automation not only streamlines the detection process but also enables early diagnosis, allowing growers to take proactive measures to mitigate disease spread and minimize crop damage.

Moreover, the availability of datasets like the one from Kaggle provides an invaluable resource for researchers to explore and develop machine learning solutions for grape leaf disease detection. These datasets contain diverse images representing various disease symptoms, allowing for the training and validation of robust classification models. Leveraging such datasets in combination with advanced algorithms can lead to the development of accurate and scalable solutions that benefit grape growers and the wider agricultural community.

In this context, our research seeks to address the need for reliable and efficient grapevine disease detection methods through the exploration and development of machine learning models. By developing a customized CNN model and comparing it with established architectures like MobileNet and VGG16,Our goal is to further automated disease identification in viticulture, giving grape producers the tools they need to protect their harvests and means of subsistence.

1.3 Rationale of the Study

Grapevine diseases pose a serious threat to the wine business, affecting grape output and quality worldwide. To ensure sustained grape production, effective vineyard health prevention and care are essential. Conventional illness detection techniques are time-consuming, subjective, and error-prone since they frequently need professional visual inspection. The advent of computer vision and machine learning techniques offers a promising solution for automated disease identification. Large-scale datasets, such as those from Kaggle, have facilitated research in this area by providing extensive image collections of grape leaves with various diseases.

The objective of this research is to create a novel method for detecting illnesses of grape leaves by utilizing a customized Convolutional Neural Network (CNN) model. To assess the model's effectiveness, it will be contrasted with previously trained models MobileNet and VGG16. With precise identification and classification of grape leaf diseases, the project seeks to make a substantial contribution to automated disease detection in viticulture.

Furthermore, Because this work advances deep learning and image processing, its ramifications go beyond the area of viticulture. Global efforts to reduce food poverty and improve agricultural resilience can be aided by using the tools and procedures used in this work for disease detection in different crops.

1.4 Research Questions

[1] What are the potential societal and environmental impacts of implementing this disease detection technology in vineyards?

[2] How does the customized CNN model compare to MobileNet and VGG16 in terms of accuracy and efficiency?

[3] How can the model be integrated into a real-time monitoring system for vineyards?

[4] How did you collect and preprocess the data? Why did you choose the specific CNN architecture?

1.5 Expected Output

The expected outputs of the study on Grape Leaf Disease Detection using Customized CNN Model :

[i] Model Performance Metrics

Detailed performance metrics, including accuracy, precision, recall, and F1-score, to assess the effectiveness of the customized CNN, MobileNet, and VGG16 in identifying grape leaf diseases.

[ii] Comparative Analysis

A comprehensive comparison of the customized CNN model with MobileNet and VGG16 to determine which model performs best in classifying grape leaf diseases.

[iii] Resource Utilization and Efficiency

Evaluation of the training time and computational resources required for each model, providing insights into their efficiency and practicality for real-world applications.

[iv] Generalization Capability

Assessment of the models' ability to maintain high performance when applied to new, unseen data from different vineyards or grape varieties, ensuring their robustness.

[v] Implementation Feasibility

Analysis of the practical aspects of integrating the models into an automated vineyard monitoring system, including challenges and solutions for real-time processing and hardware requirements.

1.6 Report Layout

Six separate chapters, each covering a significant finding from our research, make up our report. A thorough examination of the introduction, motivation, goals, expected results, problem description, study subjects, strategies, and research potential is included in Chapter One. In Chapter Two, we explore terminology, examine previous research, and offer a thorough overview of these topics. Chapter Three covers the topics covered in this section and focuses on key elements such as the introduction, research methodology, dataset, data pretreatment, split, and deep learning. Chapter Four provides a thorough analysis of these important components by focusing on the Evaluation Technique, Performance Analysis, Visualization, Model Analysis, and Result Discussion. Chapter Five delves into the societal impact, environmental implications, and outlines the sustainability plan associated with our research. Finally, Chapter Six encapsulates our concluding remarks, reflects on drawbacks encountered, and outlines avenues for future work. This structured framework ensures a comprehensive coverage of the research's various facets, facilitating a thorough understanding of our methodologies, findings, and implications.

CHAPTER 2

BACKGROUND

2.1 Terminologies

In Chapter Two, we delve into the jargon associated with our study, offering clarification and insight into important ideas. A key phrase is "grape leaf diseases," which describes a range of bacterial and fungal pathogens that impact grapevines, including leaf blight, esca, and black rot. It is imperative to comprehend these terminologies in order to accurately classify and identify diseases. Another important concept is "Convolutional Neural Network (CNN)," a deep learning technique that is often used for image recognition applications. CNNs are perfect for image classification tasks like grape leaf disease detection because of their multiple layers, which allow them to learn hierarchical feature representations from input images. "Data preprocessing" refers to the steps involved in preparing raw data for analysis by cleaning, modifying, and arranging it.The quality and adaptability of the dataset used to create the machine learning models for our study are greatly enhanced by preprocessing techniques like information augmentation and normalization. Moreover, "performance analysis" refers to the evaluation of model performance using a variety of metrics, such as F1-score, accuracy, precision, and recall. These measures shed light on the models' classification performance for grape leaf diseases. Finally, the term "sustainability plan" describes tactics meant to guarantee the long-term success and influence of our study. This may involve taking into account issues of environmental sustainability, societal effect, and ethical implications in order to make sure that our findings benefit the agriculture sector and the larger community. Gaining an understanding of these important terms is necessary to fully understand the research methods and conclusions that we have provided.

2.2 Related Works

The difficult task of identifying grape leaf diseases, which have a major influence on fruit output, is discussed in the study "SVM Classifier Based Grape Leaf Disease Detection". The study uses image processing methods, such as segmentation and texture and color feature extraction using K-means clustering. The type of leaf illness is then identified and classified using SVM classification. The suggested method diagnoses grape leaf diseases—which are mostly caused by bacteria, fungus, and viruses and are frequently challenging to manage—with an accuracy of 88.89%, indicating its efficacy in preventing fruit formation.

The article "Classification and detection of grape leaf disease" The article "Using Multi-class Support Vector Machine" discusses how to better classify leaf diseases in grape plants by utilizing Support Vector Machines (SVM). SVM was first developed for binary classification; with a little modification, it may be used for multi-class classification as well. The study uses HSI photos' ability to retain color consistency in the face of changing background lighting to improve disease classification. The primary goal of earlier research was to extract statistical features from RGB signals that were transformed into LAB format. Through the addition of HSI image attributes and the use of SVM for classification across a broader range of data points, this effort expands the database. Plant diseases have a big effect on the economy and agricultural productivity. Being a significant fruit supply high in nutrients like vitamin C, grapes are especially susceptible to illnesses that compromise their productivity and quality. Plant disease detection and classification have been effectively achieved with the application of digital vision-based techniques in subsequent years.

This research uses Artificial Bee Colony (ABC) optimization for feature selection with a focus on the identification and categorization of illnesses in grape leaves. In order to eliminate background and noise from input photos, pre-processing techniques are used. To determine the ideal feature set, color, texture, and shape-related features are retrieved and put through an ABC-based attribute selection process. In order to diagnose diseases, these particular traits are subsequently fed into a Support Vector Machine (SVM) classifier. The suggested approach performs better in terms of recall, precision, and classification accuracy than existing feature selection algorithms, as evidenced by experimental results that support its effectiveness.

In order to maximize food production, the need of identifying different diseases in leaves is discussed in the publication "Grape Leaf Multi-disease Detection with Confidence Value Using Transfer Learning Integrated to Regions with Convolutional Neural Networks"The goal of the project is to discover three grape leaf diseases—Black Rot, Black Measles, and Isariopsis—in order to enhance the availability of food. It evaluates AlexNet, GoogLeNet, and ResNet-18, three pre-trained networks, to see which works best when paired with Regions with Convolutional Neural Networks

(RCNN) for multiple item detection. Annotated pictures and ground truth tables are included with the training data. Combining AlexNet with RCNN yields better results than GoogLeNet and ResNet-18, with accuracies of 92.29% and 89.49%, respectively. Due to the fact that grapes are prone to a number of diseases that can hinder their growth and productivity, the study "Grape Leaf Disease Identification using Machine Learning Techniques" aims to address the demand for precise disease identification in crops. The automatic approach that has been suggested makes use of machine learning and image processing methods to identify illnesses in grape plants. Using grab cut segmentation, the system separates the leaf from the background images. Global thresholding and semi-supervised algorithms are then used to identify unhealthy regions. Using Support Vector Machine (SVM), Adaboost, and Random Forest tree techniques, features derived from the sick areas are identified; SVM achieves a testing accuracy of 93%.

The problem of real-time disease detection in grape plants is addressed in the publication "Real-Time Diseases Detection of Grape and Grape Leaves using Faster R-CNN and SSD MobileNet Architectures". applying two pre-trained deep learning models, Single SSD_MobileNet v1 and Faster R-CNN Inception v2, the study focuses on applying transfer learning to distinguish between healthy and unhealthy grapes and grape leaves. Achieving 78% to 99% classification accuracy, the Faster-R-CNN Inception v2 model outperformed the SSD_MobileNet v1 model in terms of processing time, but accuracy was still lower. This was especially true for photos with uniform sizes and well-organized backgrounds. Faster-R-CNN Inception v2, with its longer processing time, worked better for real-time categorization.

The influence that leaf diseases have on grape productivity and the necessity of accurate diagnosis are discussed in the paper "Identification of Grape Leaf Diseases Using Convolutional Neural Network". It uses the architecture of Convolutional Neural Networks (CNNs) to identify and categorize diseases. Python's Keras libraries are used to implement the CNN, which consists of steps for data input, feature learning, and classification. CNN proved successful in identifying grape leaf disease with an accuracy rate of 91.37% after training at a learning rate of 0.0001.

The goal of this work is to map and identify red blotch disease in grape leaves using hyperspectral imaging. The virus-caused illness causes erratic patches on the underside of leaves with pink and crimson veins; it lowers sugar accumulation in grapevines and delays harvest. In order to determine the spectral signature of red blotch disease and locate affected regions, hyperspectral imaging was used both on and off the vine. In order to differentiate diseased from healthy and dry leaves, modified reflectance and reflectance ratios at particular spectral bands were useful characteristics. This allowed for supervised classification using a support vector machine. This article uses hyperspectral imaging to identify and track the stages of red blotch disease on grape leaves.

2.3 Comparative Analysis

A thorough summary of the research gap is given in Table 1, and this data laid the groundwork for the advancement of our investigation.

Table 2.3.1 Comparative Analysis of Related Works

Sl	Title	Authors	Years	Published in	Algorithms	Data set information	Accuracy%
1	SVM Classifier Based Grape Leaf Disease Detection	Pranjali B. Padol, Anjali A. Yadav	2016	Conference on Advances in Signal Processing (CASP)	SVM Classifier	Grape leaf images were collected from Pune and Nasik regions,	88
2	Grape Leaf Disease Detection and classification Using Multi-class Support Vector Machine	Nitesh Agrawal, Jyoti Singhai	2017	2017 International Conference on Recent Innovations in Signal processing and Embedded Systems (RISE)	(SVM), K-Means Clustering	The study used a dataset of 160 grape leaf images, including healthy leaves and those with Black rot, Esca, and LBlight diseases. The images were sourced from www.plantvillage.org	90,82
3	Artificial bee colony optimization (ABC) for grape leaves disease detection	A. Diana Andrushia	2019	Evolving Systems	SVM	The research paper uses Plant Village's information as well as an self-collected dataset of grape leaves.	93
4	Grape Leaf Multi-disease Detection with Confidence Value Using Transfer Learning Integrated to Regions with Convolutional Neural Networks	Sandy Lauguico, Ronnie Concepcion	2019	2020 IEEE REGION 10 CONFERENCE (TENCON), Osaka, Japan,	AlexNet, GoogLeNet, ResNet-18	The image datasets of grape leaves with various diseases were obtained from Kaggle.com by Abdallah Ali.	95,92, 89

5	Grape Leaf Disease Identification using Machine Learning Techniques	S.M. Jaisakthi,	2019	Second International Conference on Computational Intelligence in Data Science (ICCIDS-2019)	SVM	The grape leaf images were obtained from the Plant Village website and other web sources. The images vary in size and source,	93
6	Real-Time Diseases Detection of Grape and Grape Leaves using Faster R-CNN and SSD MobileNet Architectures	Shekofa Ghoury, Cemil Sungur	2019	international Conference on Advanced Technologies, Computer Engineering and Science (ICATCES 2019)	Faster R-CNN Inception v2, (SSD) MobileNet v1	The dataset consists of images of healthy and diseased grapes and grape leaves, collected from the internet and the PlantVillage dataset.	95,59
7	Identification of Grape Leaf Diseases Using Convolutional Neural Network	Moh. Arie Hasan, Dwiza Riana	2020	Journal of Physics: Conference Series	Convolutional Neural Network (CNN)	The images were collected from Kaggle.	91
8	Detecting red blotch disease in grape leaves using hyperspectral imaging	. Mehrube Mehrubeoglu, Keith Orlebeck	2016	Proceedings of SPIE Vol. 9840, 98400D	(SVM) Classifier	The dataset used in the study for detecting For instance, to identify the signs of Grapevine Leaf Stripe Disease (GLSD), a hyperspectral sensor analyses reflectance between 350 and 2,500 nm. spectroradiometer.	87
9	Identification and Solutions for Grape Leaf Disease Using Convolutional Neural Network (CNN)	Suviksha Poojari, Deepti Sahare	2020	International Conference on Communication and Information Processing (ICCIP-2020), SSRN	Convolutional Neural Network (CNN)	The dataset consists of 1003 images divided into four classes: Black Rot, Black Measles, Leaf Blight, and Healthy Leaves.	89

10	Different Machine Learning Algorithms For Detection Of Grape Leaf Disease	Ms.M.ANITHA, Ms.K.PAVANI	2023	Volume 13, Issue 07, Jul 2023, ISSN 2457-0362	Extension Bagging, SVM	The dataset is in CSV format, containing 25 columns and 4,089 records. It includes 23 attribute columns and a class column with categories like Black rot or Esca (Black Measles).n.	93, 84

2.4 Scope of the Problem

The challenge is in promptly and properly diagnosing diseases of the grape leaf, which is essential to viticulture in order to avoid crop losses and guarantee sustainable production. Conventional techniques are time-consuming, subjective, and error-prone since they depend on professional eye assessment. Automating this process using computer vision and machine learning presents several challenges, including variations in disease symptoms, differences in leaf morphology, and varying image quality. The goal of the project is to create and enhance deep learning algorithm for identifying grape disease of the leaf, namely a tailoredCNN model, or Convolutional neural network models. In an attempt to develop an automated system for better vineyard management and production, it contrasts this model with well-known models such as MobileNet and VGG16.

2.5 Challenges

The challenges confronted within the think about of grape leaf infection discovery employing a customized CNN show are multifaceted. Firstly, the location of unpretentious or early-stage indications remains a critical jump. The dependence on a single dataset from Kaggle may not enough speak to the differences of natural conditions and grape assortments, possibly restricting the model's generalization capabilities. Furthermore, the computational assets required for preparing profound learning models on huge datasets can be restrictive, presenting potential predispositions that influence the model's execution. In conclusion, the need of real-time execution and approval in field conditions may prevent the commonsense pertinence of the demonstrate. Tending to these challenges is significant for guaranteeing the precision and unwavering quality of grape leaf infection location technologies.The challenges confronted within the ponder of grape leaf malady discovery employing a customized CNN show are multifaceted. Firstly, the discovery of inconspicuous or early-stage indications remains a noteworthy jump. The dependence on a single dataset from Kaggle may not enough speak to the differences of natural conditions and grape assortments, possibly restricting the model's generalization capabilities. Moreover, the computational assets required for preparing profound learning models on expansive datasets can be restrictive, presenting potential predispositions that influence the model's execution. Finally, the need of real-time execution and approval in field conditions may ruin the commonsense appropriateness of the demonstrate. Tending to these challenges is pivotal for guaranteeing the exactness and unwavering quality of grape leaf illness location innovations.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This work achieved a maximum accuracy of 98% using transfer learning techniques on a dataset containing four distinct categories of images.

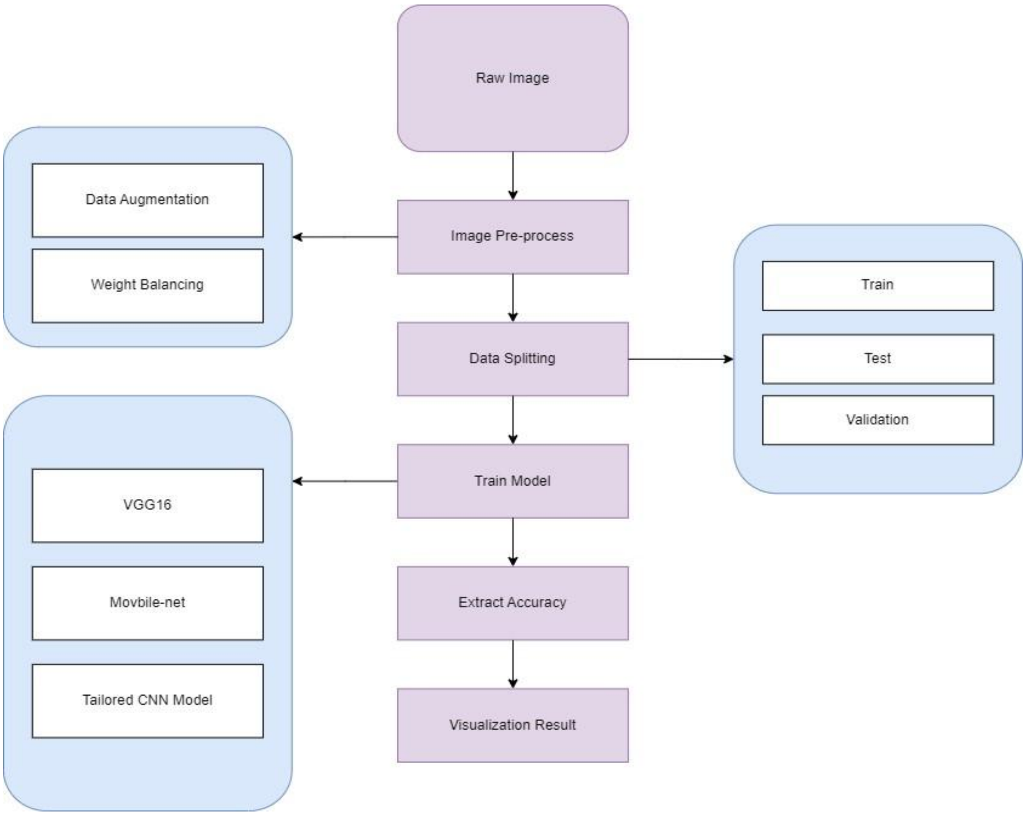

Figure 3.1.1 Methodology Process

In this section, we outline the systematic approach used to conduct our research, providing a comprehensive overview of the methods employed. Our methodology encompasses several key components,comprising gathering data, preparing it, choosing a model, training, testing, and analyzing it. Each step is vital in ensuring transparency and clarity regarding the procedures followed in achieving our research objectives.

Data Collection: the procedure for creating a varied dataset made up of photos from publically accessible sources like Kaggle that illustrate several grape leaf disease categories.

Data Preprocessing: A number of preprocessing procedures are used after data collection to enhance the dataset's appropriateness and quality. This covers methods such as data augmentation to lessen the constraints of a tiny dataset.
Model Selection: Selecting appropriate deep learning models is a critical aspect of our methodology. In this study, we utilize various Convolutional Neural Networks (CNNs), such as customized models, VGG16, and MobileNet, to assess their effectiveness.
Training and Evaluation: Using the prepared dataset, the chosen models go through a rigorous training process. They are then assessed to see how well they performed in the identification of grape leaf disease. To measure the models' efficacy, metrics like recall, accuracy, and precision are used.

3.3 Data Collection Procedure

Leaf blight, black rot, healthy, and esca are the four categories into which grape leaf diseases are divided in the Kaggle dataset, which has about 12,000 images. These photos show actual viticulture scenarios, which gives machine learning algorithms useful data for diagnosing grape leaf disease. The dataset is designed to guarantee that robust algorithms can correctly categorize diseases by means of careful augmentation and pre-processing steps.

Table 3.3.1 Sample Dataset

Healthy	**Black rot**	**Esca**	**Leaf blight**
			

3.4 Data Processing

Image pre-processing is an initial and crucial step preceding model training, making certain that picture data is prepared for a vision-based model. This step is imperative for both theoretical comprehensibility and operational efficiency, especially in Convolutional Neural Networks (CNN). Standardizing all images to the same size arrays is essential for seamless integration with fully connected layers. Pre-processing is done to improve image information by removing undesired variations and boosting specific image features that are essential for reaching higher accuracy because the original dataset might not be sufficient. Throughout this study, raw data is utilized in the pre-processing stage to prepare the images for subsequent model training.

3.4.1 Data Augmentation

Image processing is a critical step that focuses on eliminating noise and artifacts from damaged images to restore quality while retaining crucial features. This process employs various methods such as filtering and deep learning-based algorithms. In our approach, where deep learning is employed, we effectively removed noisy images from the dataset. Additionally, for Convolutional Neural Network (CNN) development, image augmentation proves beneficial by diversifying the training set without introducing new images. This technique generates replicated images through different augmentation methods, as outlined in Tables 3.5.1 and 3.5.2, illustrating the augmentation range and the amount of data that is generated for validation, testing, and training.

Table 3.4.1 Applied Augmenting Techniques in the proposed study

Augmentation Methods	**Parameters**
Rescale	1./255

Train-test split, also known as data splitting, is the act of breaking a dataset into smaller subsets for the purpose of training and evaluating models. Following this initial split, additional analyses, model training, and evaluations were conducted on these segmented subsets. The specific distribution of samples in each subset was documented to provide transparency, offering insights into how the data is allocated across different sets. During the data preparation and preprocessing phases, meticulous measures were taken to ensure appropriate partitioning of the dataset, aligning it with the requirements of subsequent project stages like model training and evaluation. Three subsets of the dataset were randomly selected: 10% for validation, 10% for testing, and 80% for training. This strategic partitioning establishes a robust foundation for the subsequent phases of the project, ensuring a well-distributed and representative dataset for comprehensive analysis and model assessment.

3.4.2 Training dataset

The term "training dataset" refers to the dataset that is used to refine the model. This sample set is essential to the learning process since it helps the model match the requirements of the classifier. Developing a classification model that successfully generalizes to new data is the ultimate objective. To find out how effectively the fitted model predicts fresh data, examples from two distinct data sources—the validation and test datasets—are used for evaluation. Data classification using variable combinations from the training dataset is made possible by supervised learning techniques. Eighty percent of the photos in this study have been used in the training stage.

3.4.3 Validation dataset

The validation set is the dataset that is typically used to assess how well a model fits into a training dataset while modifying hyperparameters. There is a chance that the evaluation will become more skewed as the model gains knowledge from the validation data during the setup phase. The validation set is often referred to as the "Dev set" or "Development set" interchangeably, indicating its function during the model's development stage. Ten percent of the photos are assigned in the validation dataset.To reduce overfitting and adjust classification parameters, a different validation dataset is used. The training dataset teaches several classifiers, the validation dataset facilitates selection and comparison procedures, and the test dataset evaluates performance metrics like accuracy and specificity.

3.4.4 Test dataset

Only post-comprehensive training on the train and validate sets is utilized as the dataset to evaluate how well the final model aligns with the training data. Though it is typical practice, it is vital to remember that using the validation set as the test set is not advised. Ten percent of the photos are in the test dataset, which is carefully selected to cover all possible variations that the model might face in real-world situations. For the sole purpose of assessing the effectiveness of a fully defined classifier, the test set functions as a specialized collection. The test set's cases are categorized using the predictions produced by the final model. Next, by contrasting these predictions with the actual classifications of the occurrences, the model's accuracy is ascertained. Once the validation and test datasets have been used, the model that was chosen at the end of the validation process is tested using the test dataset. Notably, once the original dataset has been divided into training and test datasets, the test dataset can only be utilized for the first evaluation of the model. This calculated approach guarantees a thorough assessment of the correctness and performance of the model.

3.5 Proposed Methodology

Deep learning, a subset of machine learning, enables computers to perceive the world by forming hierarchies of abstractions and learning from experience. Unlike traditional approaches, All relevant data can be defined without explicit human input; instead, the computer learns on its own through experiences. A multilevel graph that represents these hierarchies is produced by the concept hierarchy, which enables the computer to understand complex concepts by piecing them together from smaller ones. Within the domain of data science, deep learning is an essential element alongside statistics and pattern classification, collectively contributing to a comprehensive understanding and interpretation of complex datasets.

3.5.1 VGG16

An input layer, an output layer, and multiple hidden layers make up the architecture of a ConvNet, or convolutional neural network, an artificial neural network. A notable model in the ConvNet space is VGG16, which is renowned for its painstaking construction with extraordinarily small (3x3) convolutional filters—a substantial improvement over previous setups.

During training, VGG16 utilizes 80% of the total dataset, with 10% for testing and another 10% for validation. The images used in this process are standardized to a size of 50 x 50 pixels. With a batch size of 32, the training regimen spans 10 epochs and uses data augmentation methods like rotation and random flipping to increase resilience. One important result of this model is the identification of disease successfully.

VGG16, functioning as an object identification and clustering algorithm, demonstrates notable accuracy in classifying 1000 photos into 1000 distinct categories. Its popularity stems from its effectiveness in image classification, particularly when applied alongside transfer learning techniques, making it user-friendly and widely applicable.

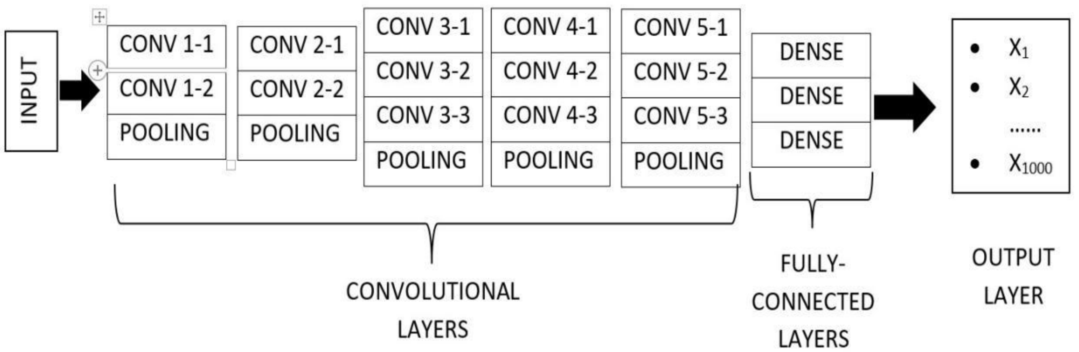

Figure 3.5.1 VGG16 Architecture

3.5.2 MobileNet

The MobileNet model is characterized by two layers of depth-wise separable convolutions, which employ a distinctive approach dividing convolutions into depthwise and pointwise categories. In the depth-wise convolution of MobileNet, each input channel is filtered by a single filter, and the outputs are subsequently combined through pointwise convolution using a 1 x 1 convolution. This straightforward depiction of the network's structure allows for a comprehensive examination to identify an optimal network configuration. In MobileNet, all layers except the final fully connected layer lack nonlinear characteristics and feed into a softmax function for classification. Batch normalization and Rectified Linear Unit (ReLU) nonlinearity continuously follow each layer. After each convolutional layer, a factorized layer with batch normalization, depthwise convolution, 1 x 1 pointwise convolution, and ReLU nonlinearity is compared to a layer with batch normalization, conventional convolutions, and ReLU nonlinearity. MobileNet utilizes strided convolution in hidden layer convolutions and the initial layer for down-sampling, with a final average pooling before the fully connected layer reducing the spatial resolution to 1. With 28 layers counting depthwise and pointwise convolutions separately, MobileNet significantly reduces convolution kernel redundancy compared to conventional 3D convolution, resulting in a smaller model size, optimized latency, and enhanced recognition accuracy.With images of size 50 x 50 pixels, the algorithm uses 80%, 10%, and 10% of the entire dataset for training, testing, and validation, respectively. With a batch size of 32, the training procedure lasts for 10 epochs and uses data augmentation methods like rotation to strengthen the model's resilience.

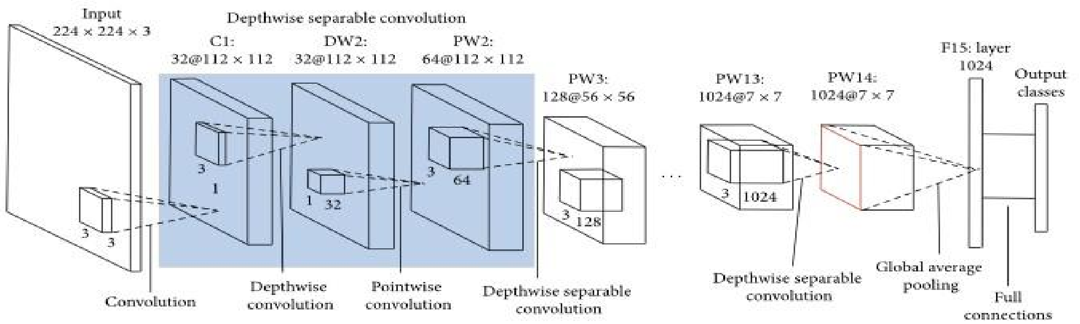

Figure 3.5.2 MobileNet Architecture

3.5.3 Customize CNN Model

A Convolutional Neural Network (CNN) model may be changed using the Keras Sequential API. Two convolutional layers prevent overfitting in the model, which takes input in the form of RGB pictures with 50x50 pixels. The 32-filter and 16-filter convolutional layers in the main set each have a 3x3 kernel and a ReLU activation function. To expedite training and normalize inputs, batch normalization is applied following each convolutional layer. Dropout layers with a 0.2 dropout rate avoid overfitting, whereas max-pooling layers decrease the spatial dimensions of feature maps. and overfitting is avoided by dropout layers with a 0.2 dropout rate, which randomly remove some input units during training.The moment set of convolutional layers consists of two filters: a 64-filter and a 128-filter, each having dropout, max-pooling, and group normalization layers. The highlight maps are aligned and fed into a thick layer that is fully associated and has 512 units with ReLU enactment following the convolutional layers. Before applying the final dense layer, which contains four units and uses the softmax activation function for multi-class classification, batch normalization and dropout layers with a dropout rate of 0.5 are applied. The accuracy metric, Adam optimizer, and sparse categorical crossentropy loss function are used to compile the model. With our customized CNN model, photographs of grape leaf diseases will be reliably classified into four categories: "leaf blight," "black rot," "healthy," and "esca."

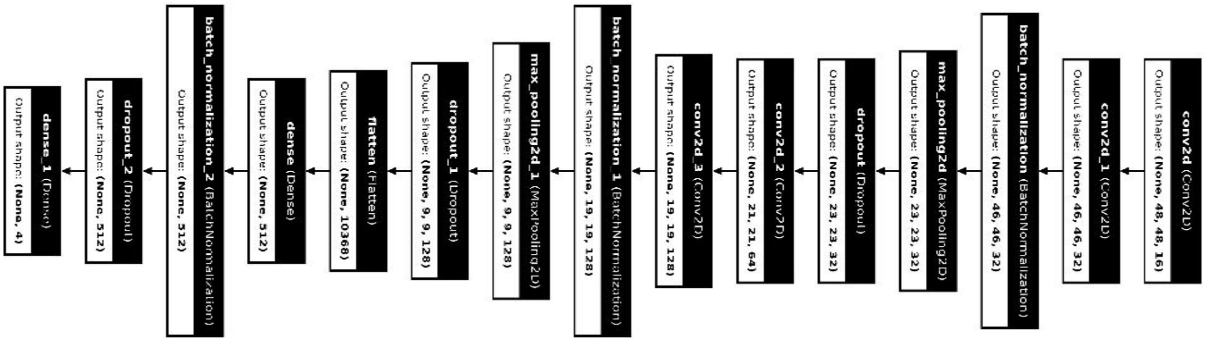

Figure 3.5.3 Customize CNN Model Architecture

3.6 Implementation Requirements

Dataset Utilization: utilizing a Kaggle dataset that has photos classified as "leaf blight," "esca," "black rot," and "healthy."

Preprocessing Techniques: Applying data augmentation and normalization to enhance model performance.

Model Comparison: Comparing an adapted CNN model to already-trained models like VGG16 and MobileNet

.**Performance Analysis:** evaluating models using measures such as F1-score, recall, accuracy, and precision to determine their effectiveness in disease detection

.

CHAPTER 4
EXPERIMENTAL RESULT AND DISCUSSION

4.1 Experimental Setup

Our work focuses on grape leaf disease diagnosis from leaf photos, mostly using deep learning methods. We used the Python-based Keras deep learning framework and TensorFlow from Google. Model construction was carried out on Kaggle's GPU infrastructure using Jupyter Notebooks, with additional support from scikit-learn, Pandas, and NumPy libraries. The dataset, consisting of around 9000 images, was partitioned into training, test, and validation sets on the Kaggle platform. The proposed model, recommended by the study, exhibited commendable performance in grape leaf disease detection.

4.2 Experimental Results & Analysis

In order to evaluate measurements and show how well supervised learning processes are, the confusion matrix, often referred to as an error matrix, is essential in deep learning. Key performance indicators such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) may be identified with its help.

4.2.1 Accuracy

The ratio of accurately predicted experimental data to all observations is the fundamental performance metric, and it can be summarized as follows.

$$Accuracy = (TP + TN) \ / \ (TP + FP + FN + TN) \tag{1}$$

4.2.2 Precision

In the context of classification problems, precision is an important parameter, especially in statistical analysis and machine learning. It expresses the percentage of positively predicted cases that are actually true positives, hence quantifying the accuracy of positive predictions generated by a model. Stated differently, precision measures the model's resistance to erroneous positives.

$$Precision = TP \ / \ (TP + FP) \tag{2}$$

4.2.3 Recall

Recall, which is also known as Sensitivity or True Positive Rate, is an important classification task measure that assesses a model's ability to capture all relevant examples of a certain class. It calculates the proportion of real positive cases that the model correctly identified. demonstrating how well it prevents false negatives.

$$Recall = TP \ / \ (TP + FN) \tag{3}$$

4.2.4 F1 Score

A key parameter in classification problems, recall (sometimes called sensitivity or true positive rate) evaluates a model's capacity to catch all pertinent instances of a given class. It expresses how much of the real positive cases the model properly detected, demonstrating how well it prevents false negatives.

$$F1\ Score = 2 \times (Recall \times Precision) \ / \ (Recall \times Precision) \quad (4)$$

4.2.5 Model Analysis

A crucial part of assessing the efficiency and performance of the created models is the model analysis component. This stage entails a detailed analysis of a number of factors to determine how effectively the models achieve the study's goals.

Table 4.2.5.1 Performance Metrics

Serial	Algorithm	Train Accuracy (%)	Train Loss	Validation Accuracy	Validation Loss
1	VGG 16	97%	0.08	0.982	0.052
2	Mobile Net	84.6%	0.39	0.82	0.53
3	Customize CNN Model	98%	0.02	0.981	0.45

Three CNN-based architectures, namely VGG16, MobileNet, and the Customized CNN Model, underwent evaluation based on several performance metrics, including Accuracy of testing, accuracy of validation, and loss in validation. The corresponding scores for these metrics are presented in Table 4.2.5.1

The Customized CNN Model emerged with the highest accuracy at 98%, showcasing superior performance compared to VGG16 and MobileNet in object detection. Both VGG16 and MobileNet demonstrated commendable accuracy, registering 97% and 84.6%, respectively. Notably, all three algorithms exhibited comparable capabilities in identifying objects closely resembling those detected by the Customized CNN Model.

In deciding the optimal method for correctly identifying the two target classes, the superior accuracy of the Customized CNN Model positions it as a promising choice. This consideration underscores the model's efficacy in object detection compared to its counterparts, emphasizing the significance of method selection for accurate identification of the specified target classes.

4.2.6 Visualization

The task returns a consecutive accuracy rate once the categorization accuracy metrics are completed. This study's accuracy and confusion matrix support the claim that the suggested model is a good fit for the TB identification job. This describes the approach taken in this project.

4.2.7 VGG16:

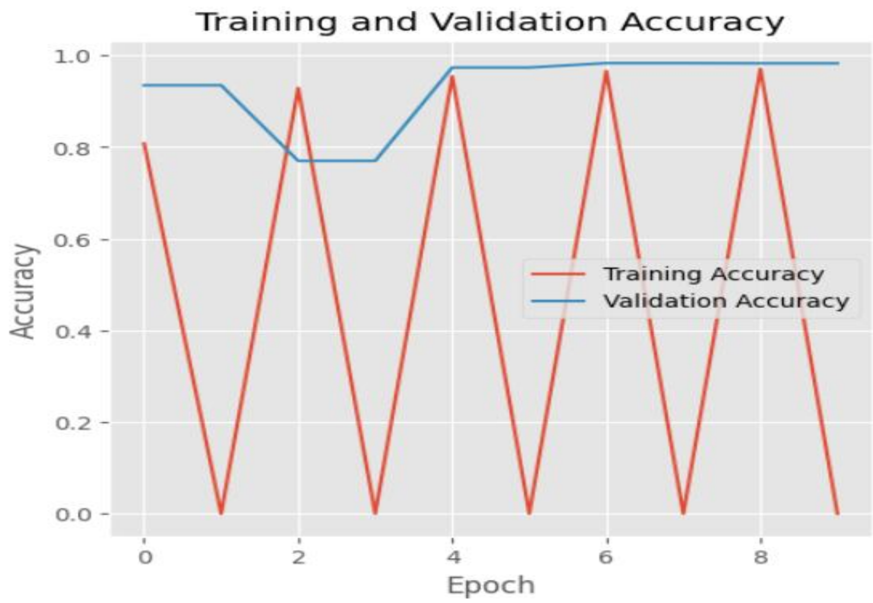

Figure 4.2.7.1 VGG16 Training vs Validation accuracy

A convolutional neural network model called VGG16 is well-known for having a deep architecture with 16 layers. It's designed with small (3x3) convolutional filters and has proven to be effective in image classification tasks. The model is popular for its simplicity and its ability to be trained on a large dataset.

Training and Validation Accuracy: 98% validation accuracy and 97% training accuracy, as well, indicate that the VGG16 model demonstrated its capacity to identify pictures and generalize to new, untested data. 10% of the dataset was utilized for testing, 10% for validation, and 80% for training in this study.

Figure 4.2.7.2 VGG16 Training vs Validation Loss

Training Loss: 0.08

Validation Loss: 0.05

These values indicate how well the VGG16 model performed during its training phase and how it generalized to new, unseen data during the validation phase. A lower loss value suggests better performance of the model.

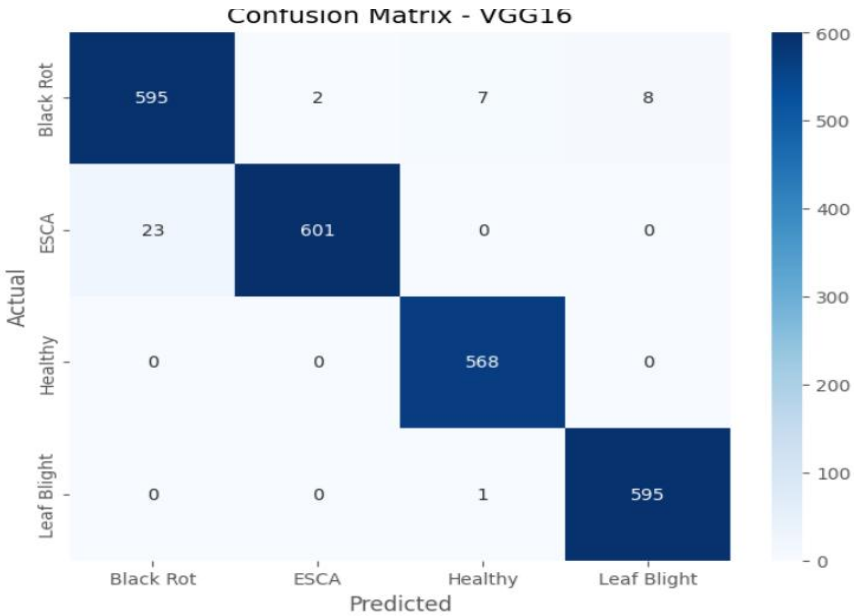

Figure 4.2.7.3 VGG16 Confusion Matrix

The grape leaf disease classification performance of the VGG16 model, comprising true positives, false positives, true negatives, and false negatives, is shown in the matrix.

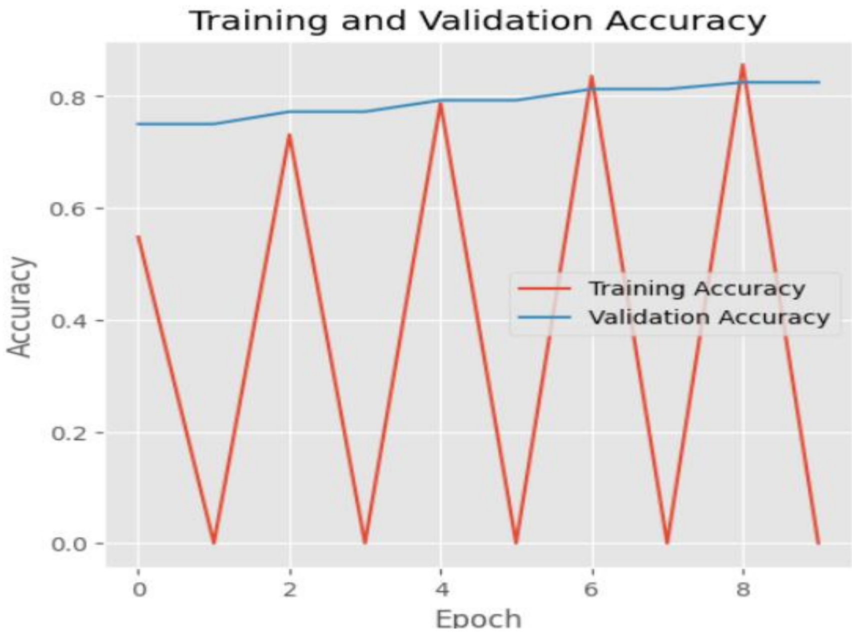

Figure 4.2.8.1 MobileNet Training vs Validation accuracy

4.2.8 MobileNet:

MobileNet is a CNN architecture known for its depth-wise separable convolutions, which divide convolutions into depthwise and pointwise types. It's designed to be lightweight and efficient, suitable for mobile and edge devices. After every layer, the model applies batch normalization, ReLU nonlinearity, and strided convolution for downsampling.

Training and Validation Accuracy: 80% of the dataset was used in the study to train MobileNet, with 10% being used for testing and the remaining 10% for validation.After resizing the photos to 50 × 50 pixels, a batch size of 323 was used for training across ten epochs. The model's validation accuracy was 82%, while its test accuracy was 84.6%.

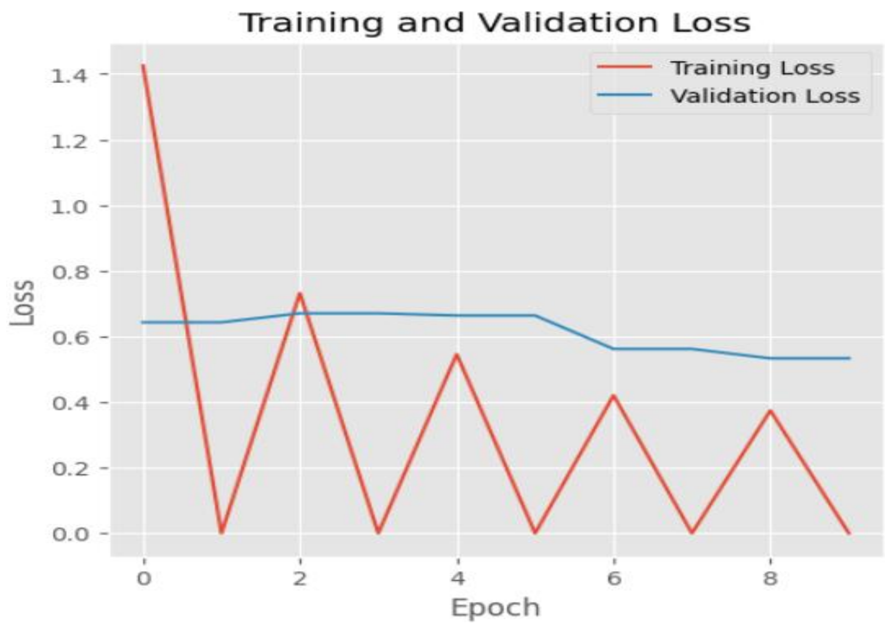

Figure4.2.8.2 MobileNet Training vs Validation Lose

Training Loss: The training loss for the MobileNet model was 0.39

Validation Loss: The validation loss recorded for the MobileNet model was 0.53 These numbers represent how well the model performed throughout the training phase. and its generalization capability on unseen data during validation. Lower loss values typically represent better model performance.

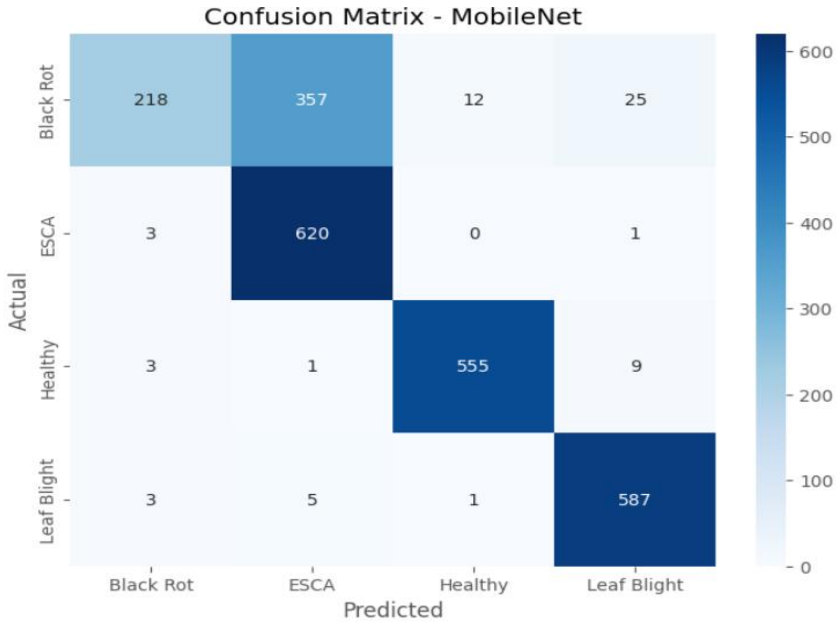

Figure 4.2.8.3 MobileNet Confusion Matric

Similar to the VGG16, this matrix displays the classification results of the MobileNet model, indicating its accuracy in identifying the correct disease categories.

4.2.9 Customize CNN Model:

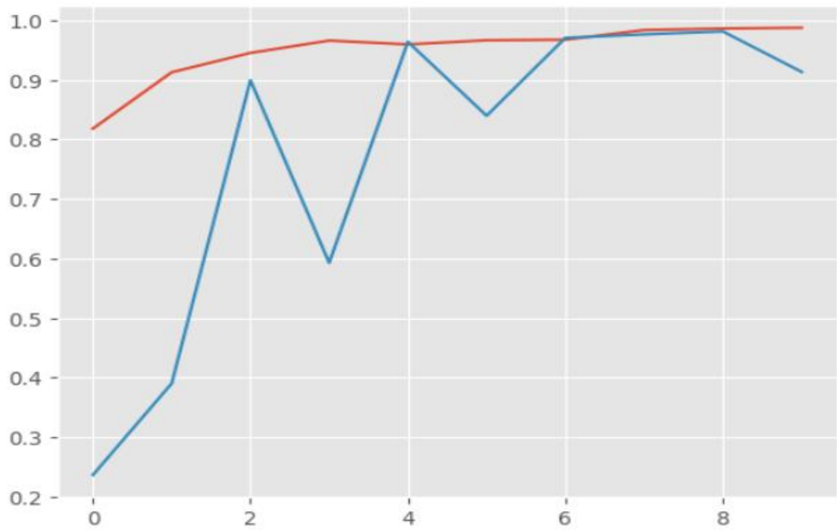

Figure 4.2.9.1 Customize CNN Model Training vs Validation Accuracy

The model's input layer is designed for RGB images with 50x50 pixels, and it is constructed using the Keras Sequential API.To avoid overfitting, it has dropout layers, batch normalization, max-pooling, and convolutional layers with filters ranging from 16 to 128.After being flattened, the feature maps are loaded into a 512-unit dense layer.

Training and Validation Accuracy: The Customized CNN Model demonstrated a training accuracy of 98%, indicating its effectiveness in learning from the dataset. Additionally, the model's excellent validation accuracy demonstrated how effectively it might transfer to fresh, untested data. Although the text does not specify the precise validation accuracy number, it does emphasize how well the model performs when it comes to grape leaf disease identification.

This model is a promising tool for diagnosing illnesses of the grape leaf because of its exceptional accuracy rate.

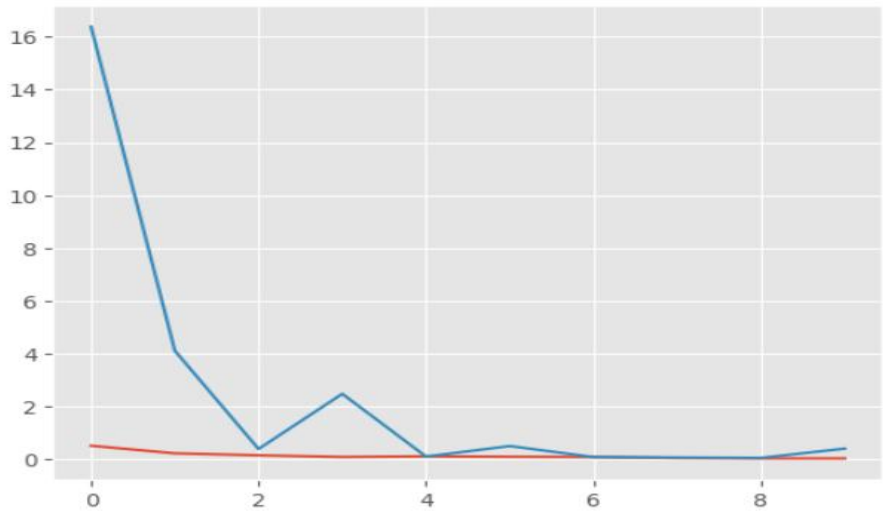

Figure 4.2.9.2 Customize CNN Model Training vs Validation Loss

Training Loss: The training loss for the Customized CNN model was 0.02

Validation Loss: The validation loss recorded for the Customized CNN model was 0.45, These numbers show how well the model performed in the training phase and how well it was able to generalize on previously encountered data in the validation phase. A lower training loss signifies that the model has learned well from the training dataset, while the validation loss provides insight into how well the model can perform on data it hasn't seen before.

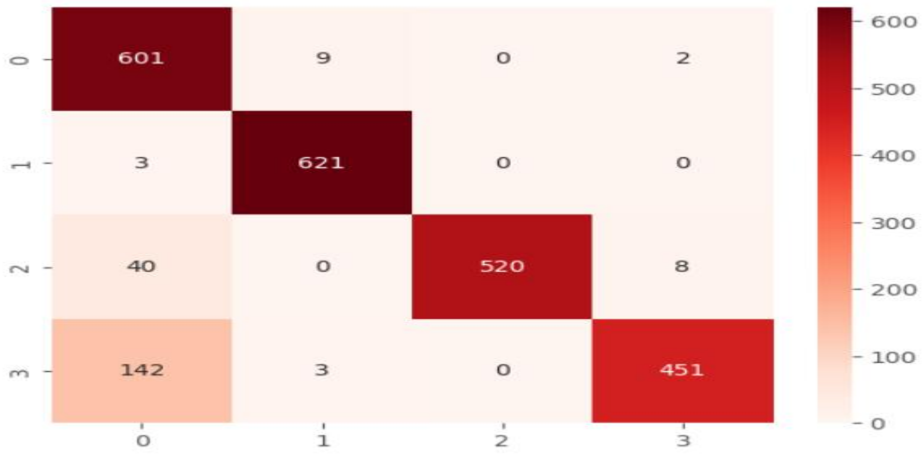

Figure 4..2.9.3 Customize CNN Model Confusion Matric

The confusion matrix for the customized CNN model provides a detailed view of its classification accuracy, highlighting its effectiveness in disease detection.

4.3 Result Discussion

The customized CNN model achieved an impressive 98% accuracy, outperforming the VGG16 and MobileNet models, which had accuracies of 97% and 84.6%, respectively. The models were assessed using accuracy, validation accuracy, and validation loss as performance metrics. To demonstrate the performance of the models, the study provided visual aids such confusion matrices, training vs. validation loss, and training vs. validation accuracy. Given its excellent accuracy rate, the customized CNN model was suggested as the most useful for identifying grape leaf disease.

CHAPTER 5

IMPACT ON SOCIETY AND SUSTAINABILITY

5.1 Impact on Society

The affect of our research on society amplifies past rural domains, potentially benefiting various stakeholders. Accurate and timely detection of grape leaf diseases can significantly enhance agricultural productivity and sustainability. By enabling early intervention and targeted treatment, our model can minimize crop losses, thus supporting the livelihoods of farmers and ensuring food security.Better methods for managing diseases may also result in a decreased need for chemical pesticides, encouraging ecologically friendly farming methods and preserving the health of ecosystems. Furthermore, with implications outside viticulture,Our research makes advancements in image processing and deep learning. It is possible to modify the methods and procedures created to identify illnesses in different crops. aiding global efforts to combat food insecurity and enhance agricultural resilience. By fostering innovation in agricultural technology, our work has the potential to drive positive socioeconomic change, improving the livelihoods of farmers and fostering sustainable agricultural practices.

5.2 Impact on Environment

Now let's discuss how the environment impacts the use of personalized CNN models in grape leaf disease detection.What part does the environment have within the utilize of lightning profound CNN models for grape leaf illness location? To address this address, the discoveries of the taking after inquire about papers are accessible: In one ponder, grape leaf disease was identified employing a Profound Convolutional Neural Organize (DCNN) demonstrate.. This model recognizes and categorizes grape disease from leaf images using RGB.Researchers and engineers can access the grape species' fruit-image dataset from the Plant Village dataset, which is used in this model. A faster DR-IACNN model, based on deep learning, has been created in a different research project to detect grape leaf disease.

5.3 Sustainability Plan

Our sustainability plan focuses on minimizing environmental impact and promoting long-term agricultural resilience. We aim to encourage the adoption of sustainable farming practices through our disease detection technology, reducing the reliance on chemical pesticides and conserving natural resources. Additionally, we plan to collaborate with agricultural communities to provide education and support for implementing eco-friendly strategies. By prioritizing environmental stewardship and community engagement, we strive to create a more sustainable and resilient agricultural ecosystem.

5.4 Ethical Aspects

Collecting leaf images for training CNN models involves data acquisition from farmers' fields. Ensuring data privacy and security is crucial.Researchers and practitioners must handle data responsibly, protect farmers' privacy, and obtain informed consent when using their images for model development.Customized CNN models should be transparent and interpret able. Farmers must comprehend the model's operation and the rationale behind its particular forecasts. The model design, training procedure, and decision-making processes should all be documented by researchers. Adoption is facilitated and trust is increased by this transparency. Unintentionally, CNN models may pick up biases from the training set. It's critical to evaluate and reduce bias. Researchers should evaluate model performance across different grape varieties, geographical regions, and growing conditions to ensure fairness.All farmers, regardless of their resources or location, should gain from the use of CNN models for disease detection. Small-scale farmers should be able to obtain the technology through efforts, ensuring equitable access to disease management tools.

CHAPTER 6

CONCLUSION, LIMITATION, FUTURE WORK

6.1 Summery Of The Study

Utilizing a customized Convolutional Neural Network (CNN) model to identify grape leaf illnesses is the main goal of the project's research. a novel technique for categorizing illnesses of the grape leaf using a modified CNN model. enhancing model performance with preprocessing techniques including data augmentation and normalization using a Kaggle dataset.The customized CNN model's accuracy, precision, recall, and F1-score are compared with those of the pre-trained MobileNet and VGG16 models. The project's objective is to improve automated disease identification in viticulture, which could have an impact on the sustainability of agriculture and the environment.

6.2 Conclusion

To sum up, our research has effectively created a strong Convolutional Neural Network (CNN) model with an astounding 98% accuracy rate for the identification of grape disease of the leaf. Make utilization of deep learning approaches and a comprehensive dataset, we have demonstrated the effectiveness of our approach in accurately classifying grape leaf diseases. The utilization of advanced image processing methods, including data augmentation and transfer learning, has further enhanced the model's performance. Our research not only contributes to the field of agricultural technology but also holds promise for addressing broader challenges in crop disease management. Moving forward, continued refinement and validation of our model in real-world settings will be crucial for its widespread adoption, ultimately benefiting farmers, agricultural communities, and global food security efforts.

6.3 Research Drawbacks

Despite the success of our research, several limitations and drawbacks should be acknowledged. Firstly, while our model achieved high accuracy, it may still encounter challenges in detecting subtle or early-stage symptoms of grape leaf diseases. Additionally, the reliance on a single dataset from Kaggle may limit the model's generalization to diverse environmental conditions and grape varieties. Furthermore, the computational resources required for training and testing deep learning models, particularly on large datasets, can be prohibitive for some researchers or agricultural stakeholders. Another limitation is the potential bias in the dataset, which may affect the model's performance and generalizability. Finally, the lack of real-time implementation and validation in field conditions may undermine the practical applicability of our model. Resolving these issues via additional study and cooperation is necessary to guarantee the accuracy and dependability of grape leaf disease detection technology.

6.4 Future Work

The shortcomings of our existing research will be the main focus of future studies. This involves using new data augmentation techniques and transfer learning methods to improve the model's capacity to identify subtle or early-stage indications of grape leaf diseases. Furthermore, broadening the dataset to encompass a greater variety of grape varietals and environmental circumstances will enhance the model's applicability. Validation in real-world settings will be necessary to evaluate the model's usefulness. Furthermore, studies will investigate how to use cutting-edge technologies for continuous monitoring and early detection of grape leaf diseases, such as Internet of Things (IoT) devices and remote sensing.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: GRAPE LEAFS DISEASE DETECTION USING CUSTOMIZED CNN MODEL

Student ID: 201-15-14236

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Grape Leafs Disease Detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**

CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project applies CNN designs that vary, deep neural networks, and data enhancement grape leaf disease detection, demonstrating engineering (K3) and specialist (K4) knowledge through transfer learning with VGG16, MobileNet, and a custom CNN, enhancing precision agriculture.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The project makes use of the engineering method through the figure of the experimental process. & design (K5). Using the CNN paradigm, the project tackles engineering practice & technology (K6).	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33] **Section:** [3.4]
				This research project demonstrates a K8 (Study Literature) by combining knowledge from current studies to improve deep learning-based grape leaf disease diagnosis.	**Page no:** [5-7]

				comprehensive understanding of current methodologies. It employs a customized CNN model and pretrained VGG16 and MobileNet models.	**Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In order to address EP-2, this study acknowledges the challenges associated with grape leaf disease detection, such as the shortcomings of conventional techniques and the difficulties in combining transfer learning with deep CNNs. It addresses difficulties in comprehending illness patterns through comparison analysis, providing information for improving diagnostic techniques. It employs a customized CNN model and pretrained VGG16 and MobileNet models.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	By carefully analyzing test results, this extension covers EP-3 and emphasizes exchange training as the selected necessary arrangement for upgrading grape leaf malady discovery in the midst of different potential approaches. It utilizes a customized CNN demonstrate and pretrained VGG16 and MobileNet models.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	The intriguing methodology of this study extends beyond the fields of computers and architecture, impacting economic diagnostics. in grape leaf infections, contributing to progressions in accuracy horticulture and plant wellbeing administration, which shows EP-4. It utilizes a customized CNN show and pretrained VGG16 and MobileNet models.	**Page no:** [16-24] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The holistic methodology of this project tackles excellent concerns by coordinating several components throughout information collection, factual examination, and proposed strategy, guaranteeing a all encompassing arrangement to tricky issues in grape leaf illness discovery, which guarantees EP-7. It utilizes a customized CNN demonstrate and pretrained VGG16 and MobileNet models.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	By using a customized CNN model, pretrained VGG16 and MobileNet models, deep learning frameworks, annotated datasets, high-performance computing infrastructure, GPUs, and ethical considerations, our project ensures systematic research and advances grape leaf disease detection through deep CNNs and transfer learning.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		My proposition paper on grape leaf infection discovery contributes to agrarian maintainability by utilizing proficient computational assets and following to moral rules for information security.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		My proposal paper on grape leaf infection location extends upon existing investigate by looking at a novel approach through a customized CNN show and pretrained VGG16 and MobileNet models. It illustrates this approach with preparatory discoveries and a comprehensive comparative investigation, advertising unused bits of knowledge into agrarian malady discovery.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	My proposition paper on grape leaf illness discovery addresses CO4 by coordination successful venture administration and monetary oversight. This guarantees fastidious arranging, asset assignment, and budget estimation for ideal utilization of assets all through the investigate lifecycle. The extend utilizes a customized CNN show and pretrained VGG16 and MobileNet models.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	My thesis paper on grape leaf disease detection demonstrates adherence to ethical principles by prioritizing data	**Page no:** [60]

3			privacy, getting informed permission, and openly recording the study procedure. This promotes ethical implementation of cutting-edge agricultural technology while ensuring responsible sharing of data and enhancing social stability. The paper utilizes a customized CNN model, alongside pretrained VGG16 and MobileNet models.	**Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	My proposal paper on grape leaf infection discovery embodies commitment to nonstop learning (CO12) and adjustment inside the rural investigate scene. It is reflected in comprehensive information collection, thorough factual examination, fastidious technique improvement, and exhaustive exploratory comes about and examination. This illustrates a commitment to continually updating and enhancing processes to handle cutting edge problems. employing a customized CNN show, at the side pretrained VGG16 and MobileNet models.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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