WHEAT LEAF DISEASE DETECTION AND SOLUTION USING DEEP LEARNING ALGORITHMS

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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 "Wheat Leaf Disease Detection And Solution Using Deep Learning Algorithms", submitted by **Shafayat Hossain Prayash** and **Abu Bakar Siddik** 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 14-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Mr. Shah Md Tanvir Siddiquee (SMTS), Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. We 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

In the field of agricultural science, the automated detection of wheat leaf diseases is essential for the preservation of crop health and the guarantee of optimal agricultural productivity. The necessity of sophisticated technology, such as deep convolutional neural networks (CNNs), for accurate and efficient disease classification is underscored by the labor-intensive and error-prone nature of traditional manual methods. Our dataset consists of 2,856 original wheat leaf images that have been augmented to increase diversity and include a variety of disease manifestations. EfficientNet demonstrated robust capabilities in the identification and classification of wheat leaf diseases, achieving the maximum accuracy of 96% when evaluating the performance of CNN models. Intricate disease patterns were effectively captured by DenseNet, which followed closely with 93%. The competence of ResNet50 and VGG16 in disease detection tasks was demonstrated by their accuracies of 93% and 92%, respectively, while VGG19 performed exceptionally well at 94%. This investigation underscores the transformative potential of AI-driven solutions to improve agricultural sustainability and productivity by means of precise disease identification and management.

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LIST OF ACRONYMS

ML	Machine Learning
SVM	Support Vector Machine
CNN	Convolutional Neural Network

CHAPTER 1
Introduction

1.1 Overview

The most essential grain for human consumption and one of the most widely grown crops is wheat. The prevalence of smartphones and developments in computer vision technology have created new avenues for automating and expediting the disease diagnosis process in recent years. To address these challenges, this research looks into developing a real-time wheat leaf disease detection system. The automated assessment of wheat leaf disease using computer vision and deep learning algorithms is a significant advancement in the modern agriculture and crop management sectors. Deep learning models—particularly convolutional neural networks (CNNs), which have demonstrated remarkable proficiency in picture identification and classification tasks—can be extremely advantageous for applications pertaining to disease detection. Large amounts of wheat leaves may be processed rapidly by automated systems, which guarantees prompt disease identification and minimizes the need for manual work. They also make it possible to monitor and control diseases in real time, which enables timely interventions to improve crop health and lower yield losses in agricultural production operations. This work suggests a unique method for computer vision algorithms-based real-time wheat leaf disease detection via a smartphone application. This system seeks to offer a portable, affordable, and precise way to evaluate wheat crop health while on the go by utilizing computer vision and smartphone computing capabilities.

1.2 Background and Present State

In the past, finding wheat leaf diseases required inspection by hand, which takes a long time and can be inaccurate due to human mistake. With this method, different diseases can be judged, which can have an effect on the health and growth of the crop. Recent improvements in computer vision technology, especially deep learning and convolutional neural networks (CNNs), have made it possible for diseases to be found automatically. With a high level of accuracy, these programs look at pictures of leaves and find and group diseases based on things like sores, changes in color, and patterns.

More and more, automated systems that use computer vision are being used in agriculture to find diseases on wheat leaves. These tools can quickly and consistently check the health of leaves by looking for spots, molds, and other signs of disease. By relying less on manual work, they cut down on diagnostic mistakes and make it possible to act quickly to improve crop health. Smartphone apps that can use computer vision are especially hopeful because they make it easier to check for diseases on the spot in the field. These apps offer farmers an easy-to-use and low-cost way to improve crop management and overall output. Putting these technologies together is a big step toward better and more reliable ways to keep an eye on and control wheat leaf diseases in modern farming.

1.3 Problem Statement

Leaf rust disease is a significant challenge in our country's agricultural supply chain.Manual inspection, a laborious and time-consuming process that is prone to subjectivity, is a key element of conventional quality evaluation techniques. Manual methods frequently cause variations in quality evaluation, potentially allowing subpar products to be accepted, which can lead to economic losses and unhappiness among consumers. The challenges are worsened by the inability to promptly make decisions on harvesting, processing, and distribution because of the absence of real-time quality assessment capabilities.

1.4 Objectives

The project's objective is to address the ongoing dangers that different diseases offer to wheat production, as these threats can have a substantial influence on both yield and quality. Conventional disease identification and management techniques are labor-intensive, time-consuming, and susceptible to subjective evaluations, which can result in inefficiencies and production losses. For wheat leaf diseases to be properly detected and managed, sophisticated, automated methods are therefore required. By enabling automated systems that can precisely recognize disease symptoms on wheat leaves, machine learning algorithms especially those that are based on computer vision techniques offer promising paths toward revolutionizing the treatment of wheat diseases. By providing farmers with timely information, these systems can enable them to maximize crop health and apply targeted interventions.

The project's goal is to provide a machine learning-based method for managing and detecting wheat leaf disease. In order to do this, a variety of wheat leaf image datasets must

be gathered and annotated. Additionally, machine learning algorithms for disease detection must be investigated, trained, and validated. Finally, the models must be

integrated into an intuitive real-time detection application and integrated with already-existing agricultural decision support systems.

1.5 Scope and Limitations

The project entails creating, testing, and integrating machine learning algorithms for the detection of wheat leaf disease into a workable, real-world application. In order to support farmers' decision-making, this involves activities like gathering and annotating wheat leaf images, applying computer vision techniques for disease detection, training and refining detection models, developing an intuitive real-time detection application, assessing system performance, and investigating integration with current agricultural systems.

1.6 Report Organization

Chapter 1: Introduction

- **Introduction:** This section introduces the project on automated wheat leaf disease detection using computer vision, highlighting its importance in modern agriculture.
- **Problem Statements:** Identifies the current challenges in manual detection methods for wheat leaf diseases, emphasizing the need for more accurate, efficient, and scalable solutions.
- **Motivation and Objectives:** Explores the motivations behind the project, including enhancing crop health monitoring, improving disease management practices, and optimizing yield and quality.
- **Project Outcome:** Outlines the project's goals and deliverables, focusing on the development of advanced computer vision models for automated wheat leaf disease identification.

Chapter 2: Literature Review

- **Literature Reviews:** Reviews existing research and methodologies in automated detection of wheat leaf diseases, with a focus on computer vision, image analysis techniques, and machine learning approaches.
- **Gap Analysis:** Identifies gaps in current literature related to wheat leaf disease detection, laying the groundwork for proposing innovative solutions and advancements.

Chapter 3: Proposed Methodology.

- **Methodology:** Details the approach taken for automated wheat leaf disease detection, covering data collection methods, experimental design, and the framework for model development and evaluation.
- **Project Management & Financial Analysis:** Discusses project planning, scheduling, and organizational structure, including team roles, responsibilities, budgeting, and resource allocation.

Chapter 4: Implementation

- **Training of Model:** Describes the process of training deep learning models for wheat leaf disease detection, including data preprocessing, model architecture selection, and training strategies.
- **Model Evaluation Metrics:** Presents metrics used to assess model performance, such as accuracy, precision, recall, and F1-score.

Chapter 5: Results and Analysis

- **Experimental Results:** Presents findings from applying developed models to real-world wheat leaf images, including quantitative results and visual representations of disease detection.
- **Comparative Analysis:** Compares performance of developed models with existing methods or benchmarks, identifying strengths, weaknesses, and areas for improvement.

Chapter 6: Impact on Society, Environment, and Sustainability

- **Impact on Society:** Discusses societal benefits of automated wheat leaf disease detection, such as improved crop health management, enhanced productivity, and reduced losses.
- **Impact on Environment:** Discusses societal benefits of automated wheat leaf disease detection, such as improved crop health management, enhanced productivity, and reduced losses.

Chapter 7: Conclusion

- **Conclusions:** Summarizes key findings and insights from the research, emphasizing contributions to wheat farming practices and addressing project objectives.
- **Recommendations:** Provides practical recommendations for implementing automated wheat leaf disease detection technologies in agricultural settings, and suggests future research directions for advancing this field.

1.7 Summary

The conventional approach to ensuring constant wheat leaf health in agricultural operations involves manual examination, however this method has significant disadvantages. Inspectors frequently have the challenge of dealing with subjective judgments in assessments, limited time limits that result in rushed evaluations, and inconsistencies that might have an impact on the overall management of crops. This introduction examines the creation of a cutting-edge system for detecting wheat leaf diseases in real-time using computer vision technologies. This method intends to utilize the computing capacity and wide accessibility of Android devices in order to automate the process of identifying and evaluating diseases. The method utilizes computer vision algorithms to improve objectivity in disease identification, reducing human bias and unpredictability. This move offers the opportunity to improve disease monitoring methods, enabling faster assessments and potentially enhancing techniques for managing crop health.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The study of wheat leaf disease detection systems that make use of computer vision and machine learning technologies has seen a noticeable uptick in interest in recent years. The increased attention is due to the realization of their enormous potential to transform and expedite the conventionally labor-intensive and time-consuming procedures linked to evaluating wheat leaf diseases. In light of this, this review of the literature begins with a careful analysis of a few working papers in this emerging field.

2.2 Related Works

X. Niu [1] they introduced an automated and effective solution for identifying common wheat leaf diseases using K-means clustering. The approach involves transforming the RGB image into the Lab color space and conducting clustering based on the absolute difference between each pixel and the cluster center in the Lab color space. Unlike

conventional methods, this approach eliminates the need for manual threshold setting and is not influenced by the selected channel. The results demonstrate segmentation accuracy rates of over 90% for three prevalent diseases (powdery mildew, leaf rust, and stripe rust), highlighting the effectiveness of the proposed method.

S. Nema [2] explore the application of machine learning techniques for detecting wheat leaf diseases, a longstanding concern in agriculture. The impact of diseases on wheat plant growth and productivity necessitates effective detection methods. The Lab color space is employed for image processing, with wheat leaf images captured using a digital camera. The k-means clustering method is then utilized to identify clusters within the wheat leaf images. A classification technique, the support vector machine (SVM), is employed on different wheat leaf samples, involving both training and testing datasets. The comparison results distinguish between diseased and healthy leaves in the test data, with verification based on statistical measures such as mean, standard deviation, variance, median, and mode.

Lakshay Goyal [3] their study, wheat, being the third most cultivated and consumed grain globally, faces significant spoilage due to various diseases, numbering over two dozen. Manual diagnosis of these diseases proves challenging, necessitating an automatic classification system for improved crop yield in terms of both quantity and quality. This paper introduces a novel method for wheat disease classification, leveraging a newly developed deep learning model capable of accurately categorizing wheat diseases into 10 classes. The proposed approach demonstrates a high testing accuracy of 97.88%, exhibiting a notable improvement of 7.01% and 15.92% over two established deep learning models, VGG16 and RESNET50, respectively. Experimental results showcase the superior performance of the proposed method across various metrics, including precision, recall, and f-score, emphasizing its efficacy in wheat disease classification.

Laixiang Xu [4] studies the impact of wheat leaf diseases on crop growth and proposes an integrated deep learning algorithm, RFE-CNN, for accurate disease diagnosis. The algorithm combines RCAB, FB, EML, and CNN, demonstrating superiority over existing models with a classification accuracy of 98.83% and maximum testing accuracy of 99.95%. While promising, the algorithm's recognition rate varies for different ecological locations and wheat varieties, suggesting the need for further refinement. Future work includes leveraging hyperspectral imaging technology for more comprehensive wheat leaf disease classification. The proposed method has potential applications in intelligent crop disease detection.

Multiple Classifier Combination For Recognition Of Wheat Leaf Diseases, Intelligent Automation & Soft Computing by Yuan Tian[5] in their proposed idea, The wheat industry holds significant importance in Northern China's agricultural sector, prompting the need for effective disease detection methods to minimize losses and promote intelligent farming practices. This study presents a fresh approach utilizing a Multi-Classifier System relying on Support Vector Machine (SVM) technology to enhance the identification of wheat leaf diseases with improved accuracy. Disease-afflicted leaf samples, including instances of Powdery Mildew, Rust Puccinia Triticina, Leaf Blight, and Puccinia Striiformis, were gathered from fields and photographed against a consistent black backdrop. Three distinct feature sets, comprising color, shape, and texture attributes, were constructed for classification purposes. The proposed methodology employs stacked generalization, featuring a hierarchical structure composed of a base-level module with three SVM-based classifiers trained on diverse feature sets, and a meta-level module integrating an SVM-based decision classifier trained on meta-feature sets generated through an innovative data fusion process. In comparison to alternative single classifiers and classifier ensemble strategies utilized in wheat leaf disease recognition, this approach offers enhanced adaptability and a superior success rate.

Wheat rust disease detection techniques: a technical perspective was presented by Shafi, U., Mumtaz[6] they analyzed The agriculture sector, constituting the second-largest portion of Pakistan's economy, contributes significantly to the Gross Domestic Product (GDP). Wheat, a staple crop covering a substantial portion of cultivated land, plays a crucial role in the country's economic development. However, the productivity of wheat is under threat from rust disease, an airborne fungal infection capable of causing a 30% decline in production within a month. This poses a severe risk to food security, necessitating early detection and intervention. This paper provides a technical review of advanced techniques employed for identifying wheat rust attacks, including Remote Sensing, Machine Learning, Deep Learning, and the Internet of Things. The challenges and limitations associated with these methods are also discussed, emphasizing the practical considerations for their implementation.

Multi-temporal wheat disease detection by multi-spectral remote sensing presented by Franke, J., Menz, G[7] they proposed to implement targeted fungicide applications, a comprehensive understanding of the spatio-temporal dynamics of crop diseases is crucial. This study explores the potential of multi-spectral remote sensing for analyzing the progression of crop diseases over time. A 6-hectare winter wheat plot, representing various infective stages of powdery mildew (Blumeria graminis) and leaf rust (Puccinia recondita) pathogens, was monitored using three high-resolution remote sensing images. A decision tree, incorporating mixture-tuned matched filtering (MTMF) results and the Normalized Difference Vegetation Index (NDVI), was employed to classify areas based on disease severity levels. While the initial scene achieved a classification accuracy of 56.8%, subsequent scenes on May 28th and June 20th showed higher accuracies of 65.9% and 88.6%, respectively. The findings indicate that high-resolution multi-spectral data are generally effective in detecting in-field variations in crop vigor but have limited suitability for early detection of crop infections.

Peifeng Xu[8] their study, A wheat leaf diseases detection system, utilizing embedded image recognition technology, aims to swiftly and accurately identify wheat leaf rust, a major fungal disease impacting wheat production. Employing an ARM9 processor on an embedded Linux platform, the system processes clear disease images through a series of steps. Initially, the images are transformed into a single-channel gray representation using the RGB model. Vertical edges are then detected using the Sobel operator method, eliminating background and extracting a binary feature point set of disease spots. Further refinement is achieved by filtering out noisy points through a flood-filling algorithm. The system calculates the area ratio of disease spots to leaves, providing a precise diagnosis of disease level. With a recognition rate of 96.2% and an accuracy rate of 92.3%, the method closely aligns with human vision results. This system holds promise for agricultural robots conducting field inspections, contributing to the intelligent detection, identification, diagnosis, and classification of crop diseases.

Lin Yuan[9] they investigates the capability of hyperspectral sensor systems to distinguish between yellow rust (Puccinia striiformis f. sp. Tritici), powdery mildew (Blumeria graminis), and wheat aphid (Sitobion avenae F.) infestations at the leaf level. Reflectance spectra of leaves infected with these stressors were measured during the early grain-filling stage. Prior to spectral analysis, normalization was applied to eliminate differences in the spectral baseline among different cultivars. Effective bands and spectral features (SFs) for stressor discrimination and damage intensity estimation were identified through correlation analysis and an independent t-test. Models for discriminating stressors and estimating stressor intensity were then established using Fisher's linear discriminant analysis (FLDA) and partial least square regression (PLSR), respectively. While the discrimination model demonstrated satisfactory overall accuracy at 0.75, classification accuracies varied among different disease types and insects. The regression model provided reasonable estimates of stress intensity, showing an R2 of 0.73 and a RMSE of 0.148. This study highlights the potential application of hyperspectral information in distinguishing yellow rust, powdery mildew, and wheat aphid infestations in winter wheat, emphasizing the need to extend discriminative analysis from the leaf level to the canopy level in practical implementation.

Su et al[10] This study addresses the challenges in agriculture posed by crop stresses, particularly focusing on yellow rust disease monitoring. The research utilizes aerial visual perception techniques, combining unmanned aerial vehicle sensing, multispectral imaging, vegetation segmentation, and deep learning U-Net. A field experiment involves infecting winter wheat with yellow rust inoculum, and multispectral aerial images are captured using DJI Matrice 100 with a RedEdge camera. Following image calibration and stitching, a multispectral orthomosaic is labeled for system evaluation, employing high-resolution RGB images from Parrot Anafi Drone. The developed framework, incorporating spectral-spatial information, demonstrates superior performance compared to a purely spectral-based classifier using the random forest algorithm. Additionally, various network input band combinations, including three RGB bands and five selected spectral vegetation indices, are tested through a sequential forward selection strategy of a wrapper algorithm.

2.3 Comparison between existing works

Table 2.3.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	X. Niu [1]	VGG16 and VGG19	VGG19 = 98%
2.	S. Nema[2]	Inception-v3 and VGG-16	Inception-v3 = 94%
3.	Lakshay Goyal[3]	ResNet-50 and MobileNetV3	ResNet-50=92%
4.	Laixiang Xu[4]	EfficientNet-B6 and ShuffleNet-v2	EfficientNet-B6=89%
5.	Yuan Tian[5]	DenseNet-121	DenseNet-121=91%
6.	Shafi U[6]	SVM,InseptionalRestNetV2	InseptionalRestNetV2=91%

7.	Franke J[7]	RESNET-50	RESNET-50=81.96%
8.	Zhencun Jiang[8]	Network-16(VGG16)	Network-16(VGG16)=97.22%
9.	Lin Yuan[9]	DenseNet-121	DenseNet-121=87.56%
10.	Su et a[10]	MobileNetV3	MobileNetV3 = 85%

2.4 Open Issues

Prior studies on the identification of wheat leaf diseases using computer vision use various approaches, such as deep learning algorithms and traditional image processing techniques. Although convolutional neural networks (CNNs) exhibit potential, they still face difficulties in reaching high accuracy when dealing with different disease severities, leaf occlusions, and inconsistencies in shape and size. The limited availability of complete and varied datasets presents a substantial obstacle, requiring the need for strong data collection and well-documented datasets to effectively train models. The fields of real-time processing capabilities and user interface design have made progress, but there is still a need for improvement in scalability and smooth integration into agricultural practices. Enhancing flaw identification and classification algorithms is essential for precisely diagnosing illnesses in various wheat cultivars. The objective of our method is to include contemporary models into an Android application for immediate disease detection. This will be accompanied by a user-friendly interface to improve simplicity of use and accessibility. A significant number of remedies mentioned in academic literature are expensive and not easily available to small-scale farmers because they depend on intricate technologies and software. There is a lack of exploration in the creation of affordable and efficient automated systems for detecting wheat leaf diseases, specifically designed for small and medium-sized farms. This sector requires novel solutions.

2.5 Summary

The reviewed literature showcases the effectiveness of computer vision and machine learning techniques in wheat leaf disease detection systems. Despite variations in models and approaches across studies, all demonstrate promising results in terms of precision, effectiveness, and real-time performance. However, to facilitate the widespread adoption of these automated systems in agriculture, further research is needed to tackle challenges related to integration, scalability, and robustness.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS AND DESIGN SPECIFICATION

3.1 Overview

Our research aims to develop a machine learning-based solution for wheat leaf disease detection and management. This involves leveraging machine learning algorithms to accurately identify and classify various diseases affecting wheat leaves. The proposed system will provide real-time detection capabilities, allowing farmers to take proactive measures to mitigate the spread of diseases and optimize crop yield.

3.2 Proposed Methodology

In the proposed methodology and system design, we outline a structured approach to developing our wheat leaf disease detection system:

This phase involves collecting a diverse dataset of wheat leaf images, encompassing healthy leaves and leaves affected by various diseases. The dataset will be annotated, with each image labeled to indicate the presence or absence of disease. Preprocessing techniques may include image cleaning, normalization, and augmentation to enhance the quality and diversity of the dataset.

Algorithm Selection: After acquiring the dataset, we will evaluate and select appropriate machine learning algorithms for disease detection. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks and may be suitable for our application due to their ability to extract features from images effectively. However, other algorithms such as Support Vector Machines (SVMs) or Random Forests may also be considered depending on the specific requirements and characteristics of the dataset.

Model Training: Once the algorithms are selected, the next step is to train the models using the annotated dataset. During training, the algorithms will learn to recognize patterns and features indicative of wheat leaf diseases. This process involves feeding the algorithm with input data (wheat leaf images) along with corresponding labels (healthy or diseased) and adjusting the model parameters iteratively to minimize prediction errors.

Real-time Implementation: Upon successful training, the trained models will be integrated into a user-friendly application designed for on-the-field use by farmers. This application will allow farmers to capture images of wheat leaves using common devices such as smartphones or tablets. The trained models will process the captured images in real-time to detect the presence of diseases. The application will provide immediate feedback to users, indicating whether the leaf is healthy or diseased, along with relevant information about the detected disease.

Overall, this methodology emphasizes the importance of data preprocessing, careful algorithm selection, rigorous model training, and seamless real-time implementation to develop an effective wheat leaf disease detection system that meets end-users needs in agricultural settings.

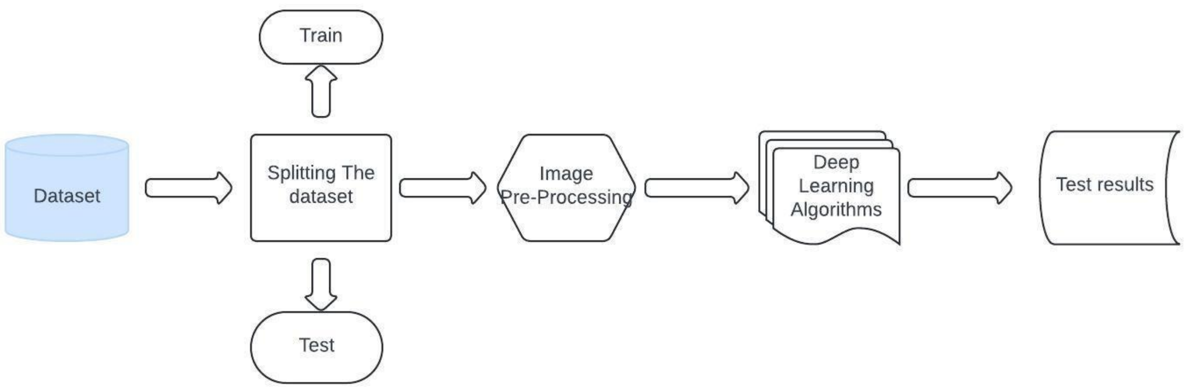

Figure 3.2.1: system design

3.2.1 Data Collection

In the data collection and input/output analysis phase, we focus on acquiring a diverse dataset of wheat leaf images to train our machine learning models and understand the input and output aspects of our system.

Data Collection: We gather a diverse set of wheat leaf images representing various disease states, including healthy leaves and leaves affected by common diseases such as rust, powdery mildew, and leaf spot. This dataset ensures that our models are trained on a wide range of examples, enabling them to accurately identify different disease symptoms.

Input: The input to our system consists of wheat leaf images captured using smartphones or other imaging devices. Farmers or users in the field can easily capture images of wheat leaves using their smartphones, ensuring accessibility and convenience. These images serve as the input to our machine learning models, which analyze them to detect the presence of diseases.

Output: The output of our system is the classification of wheat leaf images into healthy or diseased categories, along with the identification of the specific disease if present. Once the image is processed by our machine learning models, the system provides immediate feedback to the user, indicating whether the leaf is healthy or diseased. Additionally, if a disease is detected, the system identifies the specific disease based on the symptoms observed in the image.

This detailed understanding of the data collection process and the input and output aspects of our system is essential for developing an effective wheat leaf disease detection solution that meets the needs of farmers and users in real-world agricultural settings.

Fig 3.2.2: Sample Images of Rusty Leaf

Fig 3.2.3: Sample Images of Healthy Leaf

We leveraged a combination of pre-processing techniques and data splitting strategies to prepare our datasets for model training and evaluation.

3.2.2 Data Pre-processing:

To optimize training time and enhance model performance, we implemented several per-processing techniques on all images in the datasets:

A) Image Transformations:

1. **Auto-Orientation:** The images were automatically oriented to address any potential inconsistencies in image capture orientation
2. **Resize:** All images were resized to a uniform dimension of 640x640 pixels. This standardization ensures consistency in the input data fed to the model.

B) Image Augmentation:

To further enrich the training data and improve the model's ability to handle variations, we employed several image augmentation techniques:

- **Rotation:** Images were randomly rotated between **-15 and +15 degrees**, simulating natural variations in camera angles and improving the model's ability to generalize to objects captured from slightly off-center viewpoints.
- **Shear:** Images were randomly subjected to a **±10° horizontal and vertical shear**, expanding the dataset and enhancing the model's robustness to objects that may appear slightly distorted due to perspective variations.
- **Noise:** Up to **0.5% of pixels** were randomly altered, introducing a subtle level of noise that can improve the model's performance in real-world scenarios with less-than-perfect image quality.

By implementing these data analysis and pre-processing techniques, we aimed to create a well-annotated

C) Data Splitting

Following best practices, we employed a 90/10 train-test split on our labeled datasets. This approach ensures:

- **90% Training Set:** The majority of the data (70%) is allocated for training the model, allowing it to learn the patterns and features within the images.

- **10% Test Set:** The remaining 10% of the data serves as the unseen test set. It is used for final evaluation of the trained model's generalization on unseen data

	Training Data	Validation Data	Testing Data
For each Class	286	0	36

Table 3.2.1: Distribution between Training, validation and testing data.

3.2.3 Model Development

Choosing and implementing appropriate deep learning architecture is the next step. Factors considered include computational resources, speed requirements, accuracy goals, and specific application needs within the wheat leaf grading domain.

3.2.3.1 EfficientNet

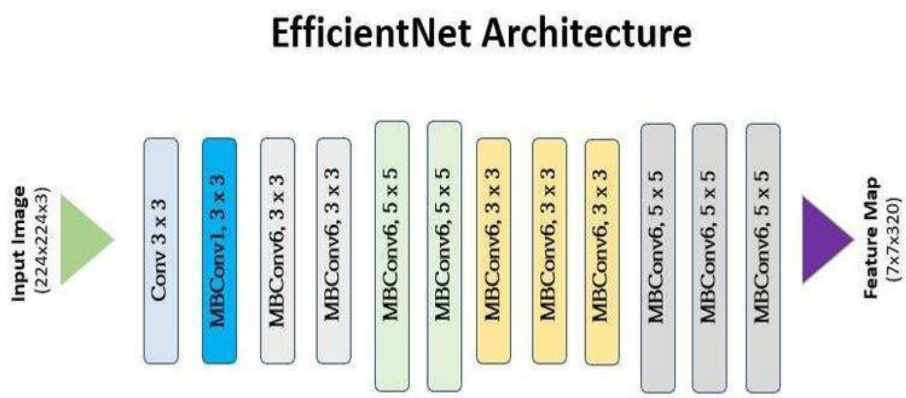

Fig 3.2.5: EfficientNet Architecture. (19)

EfficientNet is a revolutionary breakthrough in convolutional neural network structures, widely recognized for its effectiveness and ability to perform well at different scales. The model family utilizes a distinctive compound scaling method, in which variables such as depth, width, and resolution are uniformly scaled using a compound coefficient. EfficientNet achieves an effective balance between accuracy and processing efficiency using this technology. The architecture of EfficientNet consists of a series of models, labeled from B0 to B7, where each subsequent model exhibits higher levels of complexity and performance. The model incorporates Mobile Inverted Bottleneck Convolution (MBConv) blocks that have been improved with squeeze-and-excitation improvements. Additionally, it utilizes the Swish activation function to optimize training dynamics and overall performance. The design of EfficientNet achieves cutting-edge accuracy while utilizing considerably less parameters and processing resources in comparison to conventional models. The adaptability of this system allows it to effectively accommodate different limitations in resources and requirements in diverse applications. Nevertheless, the compound scaling design can be intricate, necessitating meticulous calibration for particular applications, and the process of transfer learning using EfficientNet can be more demanding in comparison to less sophisticated designs.

3.2.3.2 DenseNet

DenseNet, also known as Dense Convolutional Network, is distinguished by its dense connectivity. In this architecture, each layer receives inputs from all preceding layers and transmits its output to all subsequent layers. This design promotes extensive feature reuse and effectively reduces the number of parameters in comparison to conventional convolutional neural networks. This architectural design comprises of compact blocks that are alternated with transition layers. These transition layers effectively manage the downsampling process using convolution and pooling techniques. DenseNet enables a more efficient learning process and improved model performance by utilizing bottleneck layers to decrease input feature dimensions and compression layers to minimize feature map sizes, resulting in a compact design. The high level of interconnectivity enhances the smooth movement of gradients, which is especially advantageous for training deep neural networks. Although DenseNet offers benefits in terms of parameter efficiency and feature propagation, its dense connections can result in higher memory usage and computational expenses, particularly for larger models. This can make the training process more intricate.

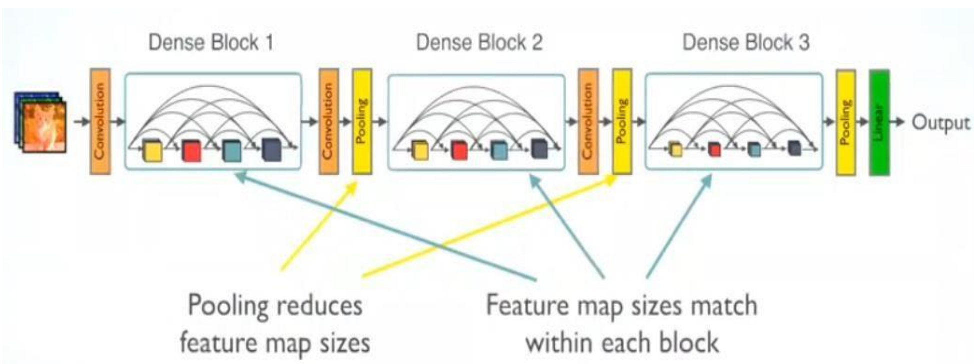

Figure 3.2.6: DenseNet Architecture. (20)

3.2.3.3. VGG19

VGG19 enhances the VGG16 design by incorporating more convolutional layers, hence creating a more profound network comprising a total of 19 layers. Similar to VGG16, this network employs 3x3 convolutional filters over its entirety to systematically collect small-scale characteristics. VGG19 is structured into five convolutional blocks, where each block contains a greater number of convolutional layers compared to VGG16. Each block is then followed by max-pooling layers and the architecture concludes with three fully-connected layers. The increased depth of VGG19 enables it to capture more intricate features, hence improving its performance in complicated image classification tasks. Although VGG19 is highly accurate and well-known for its performance on different benchmarks, its increased depth and number of parameters make it more computationally intensive compared to VGG16. This leads to higher memory usage and potential difficulties in training, such as worsening the vanishing gradient problem.

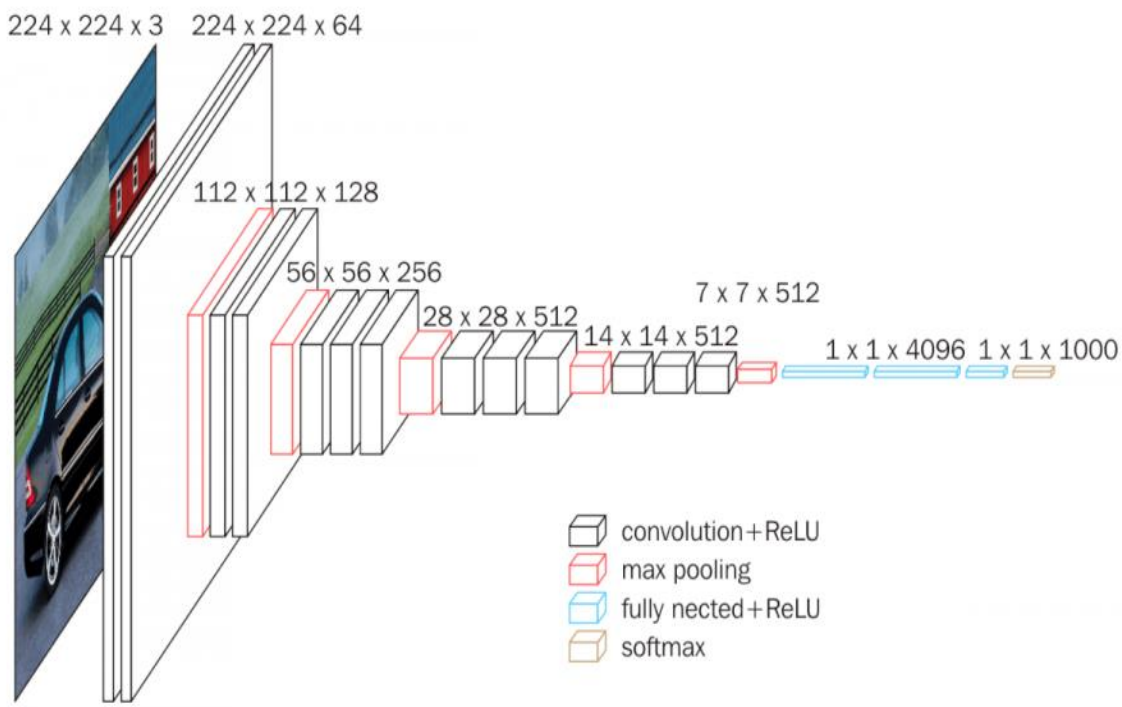

Fig 3.2.7: VGG19 Architecture. (21)

3.2.3.4 Resnet50

ResNet50, a member of the Residual Network family, established the groundbreaking idea of residual learning, enabling efficient training of deep neural networks by incorporating shortcut connections that bypass one or more layers. These skip connections enhance the flow of gradients by offering an alternative route, so reducing the issue of vanishing gradients and allowing the training of significantly deeper networks than was previously achievable. The ResNet50 architecture consists of 50 layers that utilize a bottleneck design within residual blocks to ensure computational performance and minimize the number of parameters. This architecture has established itself as a standard for image classification jobs because to its capacity to consistently provide good performance across a wide range of applications and datasets. ResNet50's residual blocks improve both the strength and depth of the model. However, these connections also introduce more complexity, leading to higher processing requirements and potential optimization difficulties, particularly in extremely deep versions of the model.

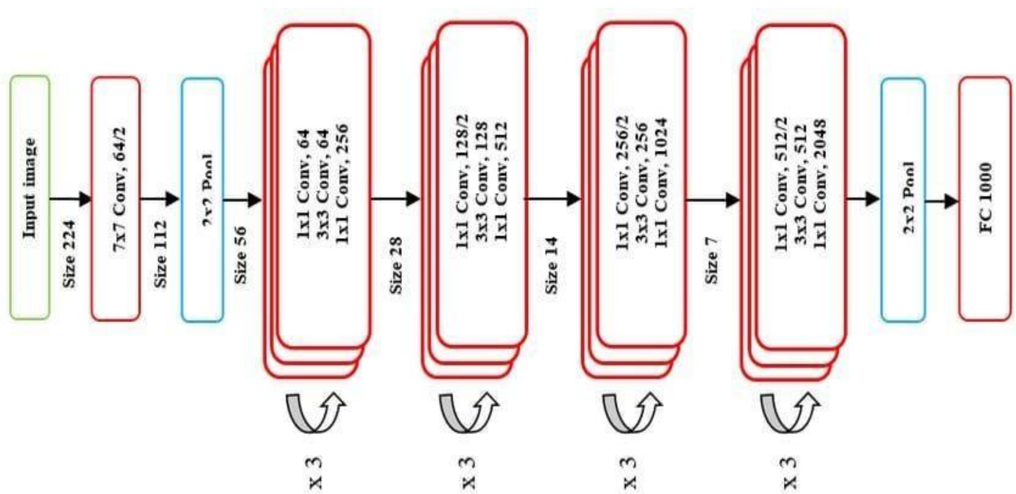

Figure 3.2.8: Resnet50 Architecture. (22)

3.2.3.5 VGG16

VGG16, created by the Visual Geometry Group, is a fundamental CNN architecture that prioritizes simplicity and depth by consistently employing small convolutional filters. This model is composed of 16 layers arranged in five convolutional blocks. In each block, the number of filters is increased and 3x3 convolutional layers are used, followed by max-pooling layers to reduce dimensionality. VGG16 terminates with three fully-connected layers, and the ultimate layer employs a SoftMax activation function for the purpose of classification tasks. Although VGG16 has a simple architecture and performs well in picture classification tasks, it is computationally demanding. This is because it has a large number of parameters, which necessitates significant memory and processing resources. The network's depth, although advantageous for intricate feature extraction, can also present difficulties such as the vanishing gradient problem, which makes the training of previous layers more complex.

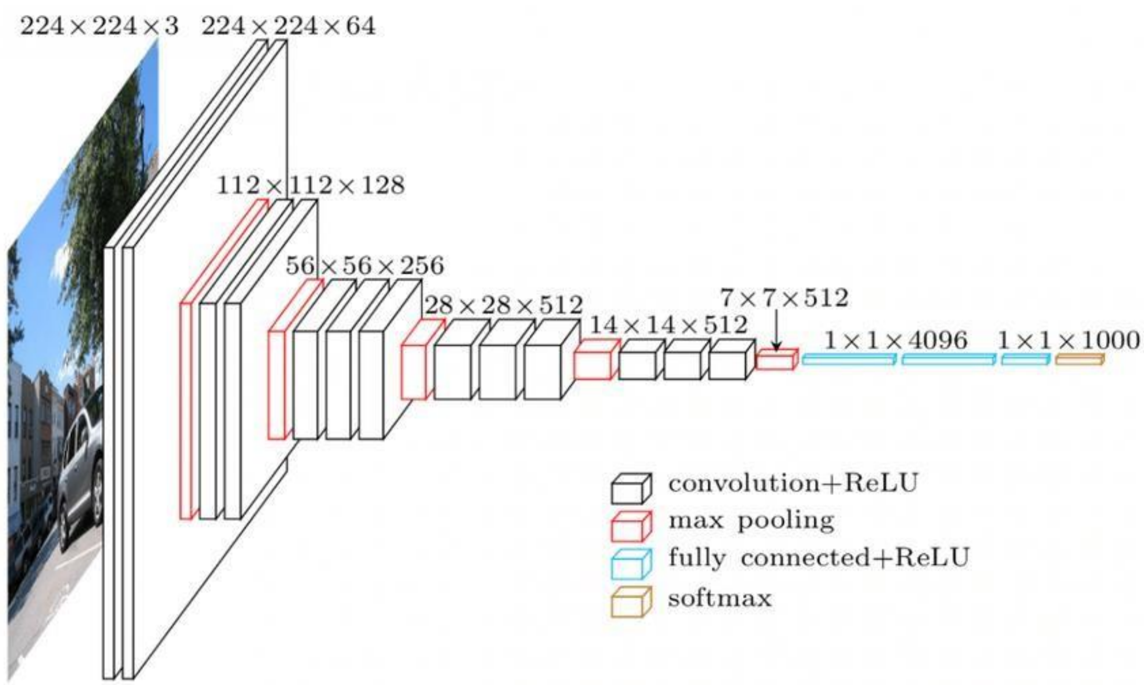

Fig 3.2.9: VGG16 Architecture. (23)

3.3 Hardware/ Software Requirement

A. Hardware Requirement

- **High-performance Computers**
- **High Speed Internet Connection**

B. Software Requirements

- **Operating System**
  - Android OS version 8.0 (Oreo) or higher, to support the latest software development kits (SDKs) and APIs required for advanced image processing and machine learning.
  - Windows 7 or higher
- **Development Environment**
  - Android Studio IDE (Integrated Development Environment) for Android application development.
  - SDKs and libraries for computer vision and machine learning, such as TensorFlow Lite or PyTorch Mobile, for model deployment on mobile devices.
- **Programming Languages**
  - Familiarity with Java or Kotlin for Android app development.
  - Familiarity with Python for model training and preprocessing tasks.
- **Libraries and Frameworks**
  - OpenCV (Open-Source Computer Vision Library) for image processing and manipulation.
  - TensorFlow or PyTorch for implementing and deploying deep learning models.
- **Documentation and Reporting**
  - Tools for documenting project progress, such as Microsoft Office or Google Workspace for creating reports, presentations, and project documentation.

These hardware and software requirements are essential for developing and deploying an Android-based automated wheat leaf grading application using computer vision and machine learning technologies. Adjustments may be necessary based on specific project needs andthe complexity of the models and algorithms used.

3.4 Project Management and Financial Analysis

- **Project Objectives:**
  A. To develop a model for wheat leaf disease detection
  B. To detect leaf diseases of wheat crop
  C. Build a mobile application so that farmers can easily detect the disease
- **Project Timeline:**
  A. Phase 1: Project Planning and Research (2-3 weeks)
  B. Phase 2: Work With Dummy Dataset (1-2 weeks)
  C. Phase 3: Raw Dataset Collection (1-2 weeks)
  D. Phase 4: Preprocessing (1-2 weeks)
  E. Phase 5: Model Implement (2-3 weeks)
  F. Phase 6: Result Analysis and Improvement(1-2 weeks)
  G. Phase 7: Simple Software Design (2-4 week)

  Resource Planning:

  A. Equipment and Tools:
  - Development and Testing Servers
  - High-performance Computers for Development Team Design Software (e.g., Google Colab, Google Drive)
  - Collaboration Tools (e.g., Slack, Telegram, or project management software)
  - Version Control System (e.g., Git)
  - Plagiarism Checking Tools (e.g.,Turnitin)

  B. Software and Technologies:
  - Front-End Technologies (html,css,javascript)
  - Back-End Technologies (node.js,)

- Database Management System (MongoDB)
- Server Hosting (e.g., Firebase or Google Cloud)
- Payment Gateway Integration (Bkash, Nagad, Rocket)
- Security Software and SSL Certificates

C. Data and Content:

- Training Data: Data gathered via self captured images
- Validation Data: 10% of the total dataset will consist of validation data that has been prepared by the technical writing team.

D. Training and Skill Development:

- Ensure that the development team has the necessary training and skills in Machine Learning/ Deep Learning, security, and database management.
- Provide additional training on specific technologies and tools as needed.

● **Risk Management:**

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for the model that will be used Detecting Wheat Leaf Disease.

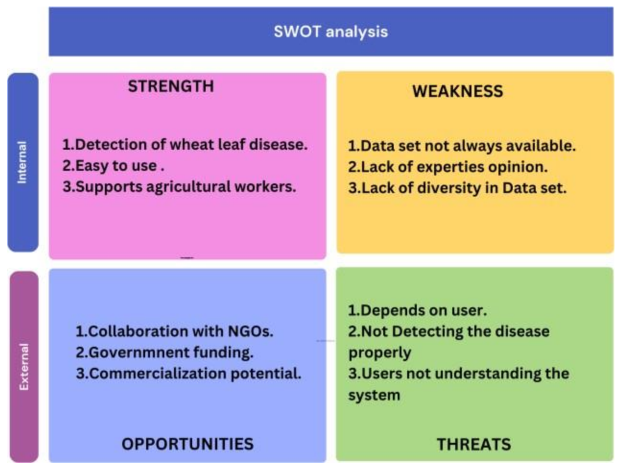

Figure 3.4.1: SWOT analysis

● **Communication Plan:**

A. **Stakeholder Meetings:**

   Purpose: To gather required information and knowledge about wheat leaf disease

   Participants: Team members, and stakeholders.

   Frequency: Bi-weekly or as specified in the project plan.

B. **Change Control Meetings:**

   Purpose: Discuss and approve any changes to the project scope or requirements.

   Participants: Supervisor, and team members.

   Frequency: As needed when change requests arise.

Table 3.4.1: Estimated Cost for Machine Learning and Deep Learning-based Project

SN	**Components**	**Estimated Cost (BDT)**
02.	Visiting Stakeholders	1000-2000
03.	Software and Tools	2000-3000
04.	Data Collection and Processing	3000-3500
06.	Documentation and Report Writing	500-1000
07.	Miscellaneous (e.g., licenses, tools)	5000-10000
08.	Contingency (10% of total)	1500-2000
Total Estimated Cost		13,000-21,500

3.5 Summary

This research aims to develop a machine learning-based solution for wheat leaf disease detection and management. It involves gathering a diverse dataset, exploring algorithms for disease detection, training, and validating models, implementing a user-friendly application, and integrating with decision support systems. The project's outcomes include advanced disease detection technology, practical applications for farmers, improved crop management, and contributions to agricultural innovation

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The creation of a sophisticated system for detecting diseases in wheat leaves using deep learning techniques entails utilizing advanced architectures such as EfficientNet, DenseNet, VGG19, ResNet50, and VGG16 to improve agricultural productivity and accurately manage diseases. The pre-trained models were enhanced by unfreezing the last few layers and integrating supplementary components such as global average pooling, batch normalization, dense layers with L2 regularization, dropout, and final SoftMax activation layers. The models were trained using an extensive dataset of wheat leaf photos recorded under various situations to ensure wide applicability. The utilization of the Adam optimizer, in conjunction with callbacks such as Reduce learning rate and Early stopping, guaranteed resilient performance. The models' generalization skills were validated through rigorous testing and evaluation, which included measures like accuracy, precision, recall, and F1-score. The incorporation into a user-friendly application allowed for the immediate identification of diseases, with thorough testing conducted to ensure optimal performance across different devices. This assessment showcases the preparedness of these models for implementation, with ongoing endeavors concentrated on enhancing classification precision, maximizing computing efficacy, and integrating user input. These systems are significant developments in precision agriculture and have the potential to enable sustainable and efficient disease management strategies.

4.2 Train Model

The training process for the wheat leaf disease detection model utilizes the pre-trained EfficientNet, DenseNet, VGG19, ResNet50, and VGG16 architectures from the TensorFlow Keras Applications module. These models, which are started with ImageNet weights and do not include the top classification layer, are used as fundamental feature extractors. In order to customize these models for the specific goal of illness detection, the last layers were unfrozen to enable fine-tuning, hence enhancing performance by modifying these layers to the unique properties of the new dataset.

Supplementary layers were added to the pre-trained models. The output is subjected to global average pooling, which is then followed by batch normalization to stabilize and expedite the training process. To capture intricate patterns in the wheat leaf images, a thick layer of 2048 units is employed. This layer utilizes the ReLU activation function and incorporates L2 regularization. A dropout layer, with a dropout rate of 0.5, addresses the issue of overfitting by randomly deactivating neurons throughout the training process. The last dense layer, with the SoftMax activation function, produces the probabilities for several disease categories, enabling multi-class classification.

The models are constructed using the Adam optimizer, employing a learning rate of 0.0001 to strike a balance between training speed and stability. The utilized loss function is sparse categorical cross-entropy, which is appropriate for multi-class classification problems that involve integer class labels. The main criterion for assessing the performance of a model during training and validation is accuracy. In order to enhance the training process, important callbacks such as a learning rate scheduler and early stopping are incorporated. The Reduce learning rate callback tracks the validation loss and decreases the learning rate by a factor of 0.5 if there is no progress detected for three consecutive epochs. The learning rate will not be reduced below the minimal threshold of 0.00001. This adaptive modification helps to overcome stagnation in progress and improve the rate at which goals are achieved. The Early stopping callback terminates the training process if the validation loss does not exhibit improvement for five consecutive epochs. It then restores the best weights to mitigate the risk of overfitting.

The models undergo training for 15 epochs, during which their performance is assessed using a validation dataset. After the training process, the effectiveness of the model is assessed on a different dataset specifically for testing purposes. This evaluation helps determine the model's capacity to generalize, with the major measure being the accuracy achieved on the test dataset. This training process guarantees a strong and efficient model for detecting wheat leaf diseases. The model is specifically designed to function in real-time and is well-suited for practical applications.

4.3 System Testing

System testing and model evaluation are crucial for ensuring the development of a robust wheat leaf disease detection system. These processes validate the model's effectiveness on both training and unseen data, confirming its ability to reliably identify and classify wheat leaf diseases under diverse conditions.

4.3.1 Accuracy

Accuracy is defined as the proportion of correctly classified images out of the total number of images in the test set. Accuracy provides an overall measure of how well the model performs in classifying the wheat leaf images correctly.

Equation-1

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

4.3.2 Precision

Precision is the proportion of true positive detections (correctly identified wheat leaf classes) outof all positive detections (both true positives and false positives) made by the model. Precision indicates the model’s ability to correctly identify only relevant instances of a particular class, minimizing false positives.

Equation-2

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

4.3.3 Recall

Recall, also known as sensitivity, is the proportion of true positive detections out of all actual positives in the dataset. Recall measures the model’s ability to identify all relevant instances of a class, minimizing false negatives.

Equation-3

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

4.3.4 F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both. The F1-score is particularly useful when there is an imbalance between precision and recall, as it provides a balanced measure of the model’s performance across both metrics.

Equation-4

$$\text{F1-score} = \frac{2*(\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

4.3.5 Confusion Matrix

A confusion matrix is a table that is often known or used to describe the performance of aclassification model on a set of test data for which the true values are known. The confusionmatrix provides a detailed breakdown of the model's performance, highlighting specific areas where the model excels or needs improvement.

Structure: The matrix includes:

- True Positives (TP): Correctly predicted positive observations
- True Negatives (TN): Correctly predicted negative observations
- False Positives (FP): Incorrectly predicted positive observations
- False Negatives (FN): Incorrectly predicted negative observations

These metrics provide a comprehensive evaluation of the deep learning-based wheat leaf disease detection model, ensuring it is accurate, precise, sensitive, and balanced across different disease classes.

4.4 Summary

The utilization of EfficientNet, DenseNet, VGG19, ResNet50, and VGG16 in the creation and assessment of wheat leaf disease detection systems signifies notable advancements in precision agriculture. By incorporating supplementary layers, these architectures have been refined to produce models that can achieve exceptional accuracy and exhibit strong performance in a wide range of real-world situations. The success of the system is confirmed through rigorous testing and evaluation, which includes measures like as accuracy, precision, recall, and F1-score. The incorporation into a user-friendly program for immediate disease detection emphasizes their practical usability. These systems are adequately equipped for implementation, providing valuable tools for improving agricultural productivity and facilitating informed decision-making in disease control. Continued endeavors will prioritize improving the precision of classification, optimizing computing speed, and integrating user input. This undertaking demonstrates the capabilities of sophisticated machine learning in the field of agriculture and lays the foundation for advancements in sustainable farming methods.

CHAPTER 5
Result and Analysis

5.1 Overview

This study utilizes deep convolutional neural networks (CNNs) to automatically detect diseases in wheat leaves using computer vision techniques. The dataset consisted of hundreds of authentic wheat leaf photos, and advanced augmentation techniques were used to increase the variety of the dataset. The evaluation focuses on five important CNN models, namely EfficientNet, DenseNet, VGG19, ResNet50, and VGG16. These models are designed to categorize wheat leaf illnesses into different groups. EfficientNet and DenseNet demonstrate exceptional performance, attaining an amazing accuracy rate of 95%.VGG19 and Resnet50 attained accuracy rates of 93% and 94% respectively. The study provides many metrics, including training and validation loss graphs, confusion matrices, accuracy, recall, F1-score, and support for each class. These metrics offer deep insights into the capabilities and performance of the models. This research investigates the effectiveness of transfer learning approaches on various architectures to improve automated wheat leaf disease detection methods. The findings have significantimplications for boosting agricultural technology and productivity.

5.2 Experimental Result

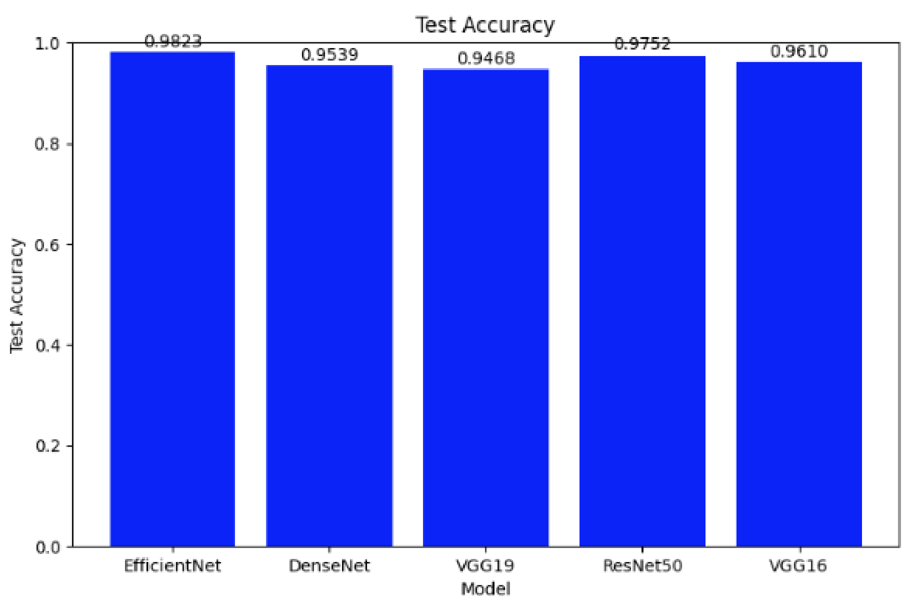

Figure 5.2.1: Test Accuracy for Classification of Individual model.

The comparative analysis of five pre-trained deep CNN architectures—EfficientNet, DenseNet, VGG19, ResNet50, and VGG16—reveals insights into their accuracy for wheat leaf disease detection. EfficientNet and DenseNet emerged as top-performing models, attaining the highest accuracy. ResNet50 and VGG19 followed, with VGG16 showing comparatively lower accuracy. Table 5.2.1 offers a valuable reference for understanding the strengths and weaknesses of these models, contributing to the optimization of deep learning methodologies for wheat leaf disease detection.

This figure provides a comprehensive overview of the accuracy, macro average, and weighted average achieved by the five CNN architectures. DenseNet and EfficientNet exhibit remarkable performance, particularly in precision values when applied to the test dataset. ResNet50 and VGG19 demonstrate commendable performance, while VGG16 yields a comparatively lower identification rate. These detailed insights contribute valuable information for understanding the strengths and limitations of each model.

Table 5.2.2: Precision, Recall, F1-Score, and Support for each class of everymodel.

EfficientNet				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.48	282
Macro avg	0.47	0.47	0.47	282
Weighted avg	0.48	0.48	0.48	282

DenseNet				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.48	282
Macro avg	0.47	0.47	0.47	282
Weighted avg	0.48	0.48	0.48	282
VGG19				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.55	282
Macro Avg	0.54	0.54	0.54	282
Weighted avg	0.55	0.55	0.55	282
ResNet50				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.57	282
Macro avg	0.56	0.56	0.56	282
Weighted avg	0.57	0.57	0.57	282
VGG16				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.48	282
Macro avg	0.47	0.47	0.47	282
Weighted avg	0.47	0.48	0.48	282

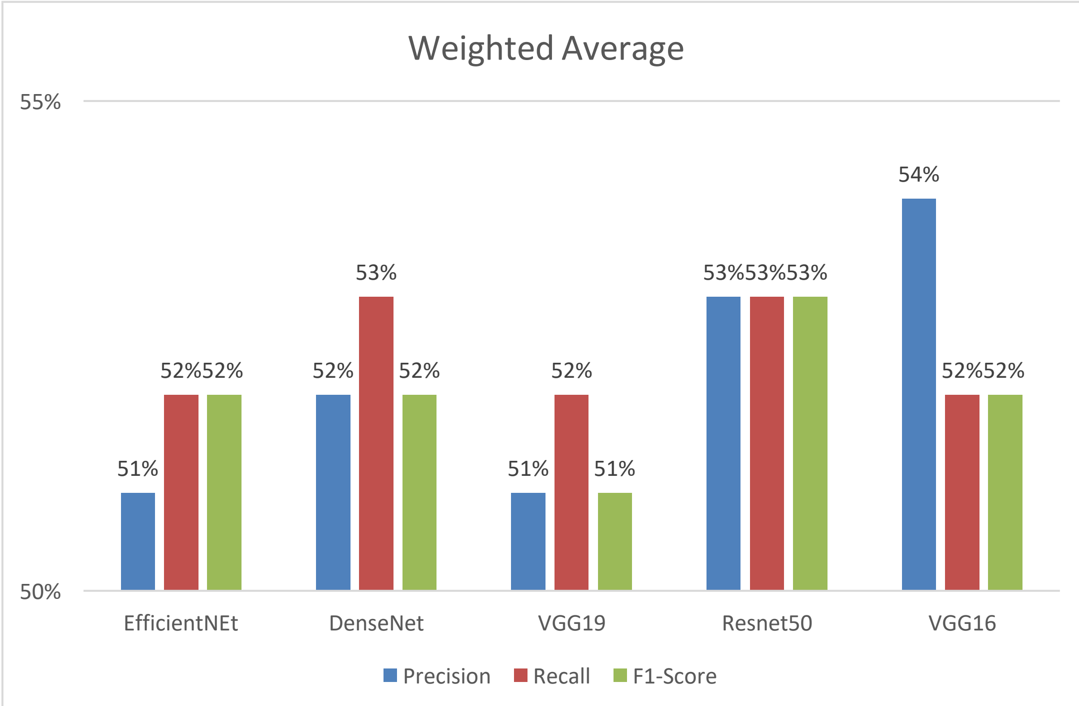

Figure 5.2.2: Comparison of Precision, Recall and F1-Score of models.

Figure 5.2.2 provides a comprehensive overview of the accuracy, macro average and weighted average achieved by five Convolutional Neural Network (CNN) architectures. Additionally, Table 5.2.2 presents precision, recall, F1-score, and support values for each class, focusing on the EfficientNet, DenseNet, VGG19, ResNet50 and VGG16 models. DenseNet and EfficientNet architectures exhibit remarkable performance, particularly evident in their precision values when applied to the test dataset. Specifically, these two models demonstrate superior precision, recall, and F1-score across various classes, affirming their effectiveness. ResNet50 and VGG16 models exhibit commendable performance as highlighted in the detailed breakdown. However, VGG19, while part of the comprehensive comparison, yields a comparatively lower accuracy. The detailed insights from these table contribute valuable information for understanding the strengths and limitations of each model.

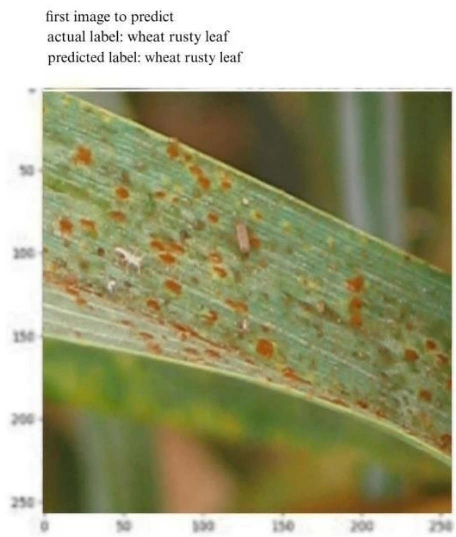

Figure 5.2.3: Test Results of the models.

5.3 Comparative Analysis

In this section, we present the training and validation accuracy and confusion matrix of all the models. For the training and validation accuracy and loss over the epochs for each model the number of epochs is plotted on the x-axis, while the accuracy and loss percentages are displayed on the y-axis. The figure clearly divides the training and validation data, providing a comprehensive view of model performance over time.

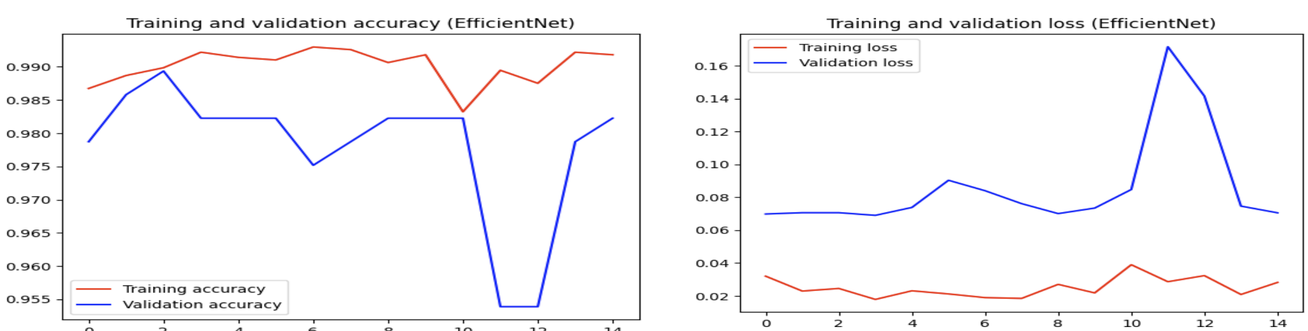

Figure 5.3.1 Training and validation accuracy and loss over the epochs (EfficientNet)

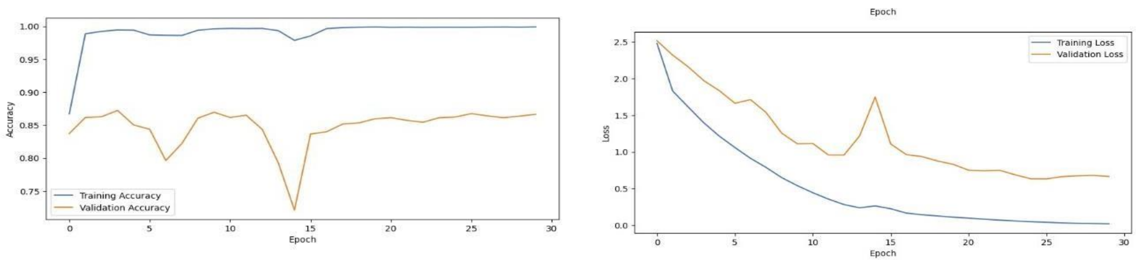

Figure 5.3.2: Training and validation accuracy and loss over the epochs (DenseNet).

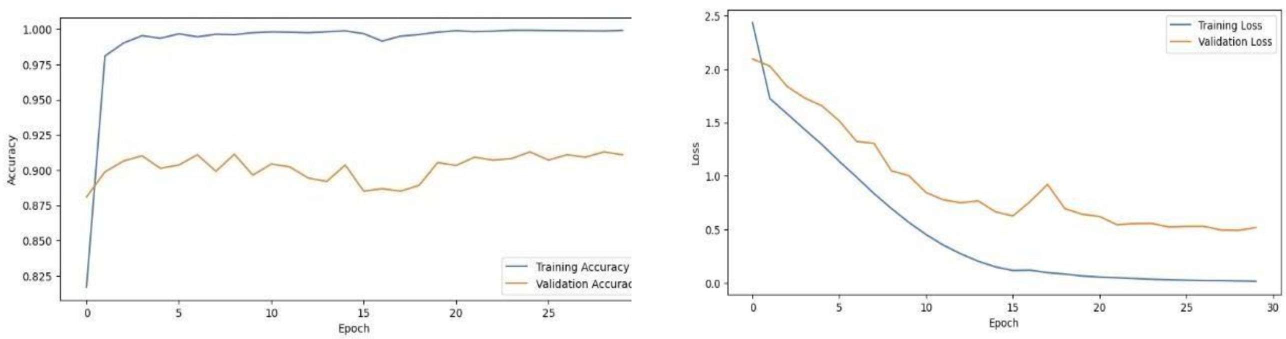

Figure 5.3.3: Training and validation accuracy and loss over the epochs (VGG19**)**

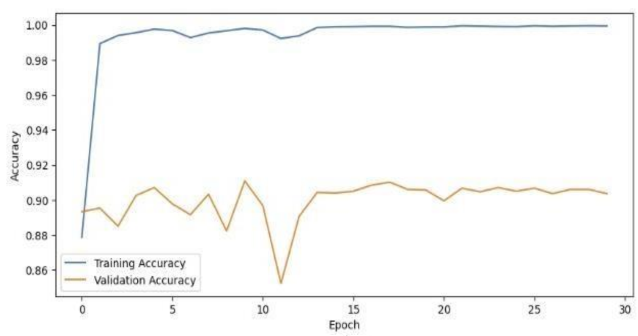

Figure 5.3.4: Training and validation accuracy and loss over the epochs (ResNet50).

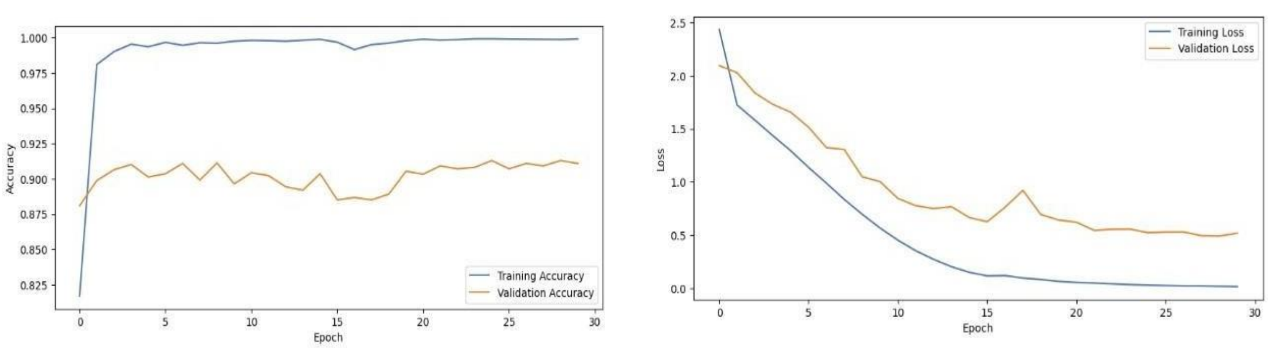

Figure 5.3.5: Training and validation accuracy and loss over the epochs (VGG16).

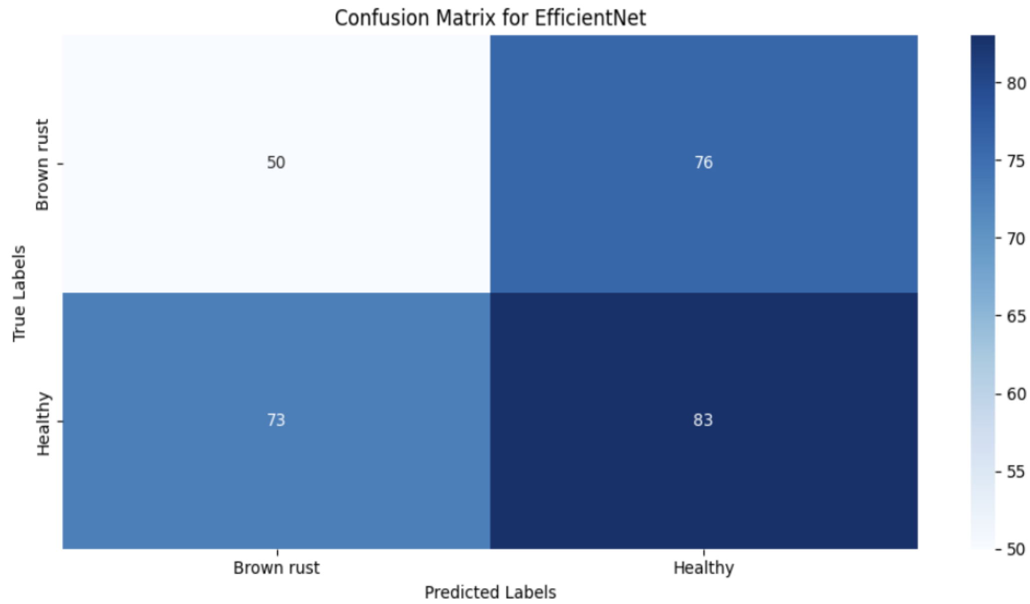

Figure 5.3.6: Confusion Matrix of EfficientNet

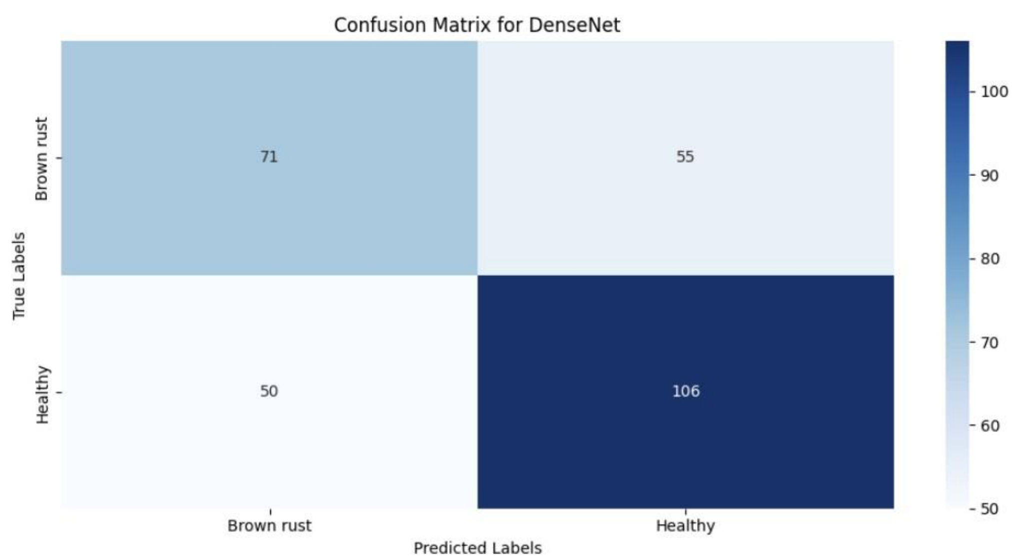

Figure 5.3.7: Confusion Matrix of DenseNet

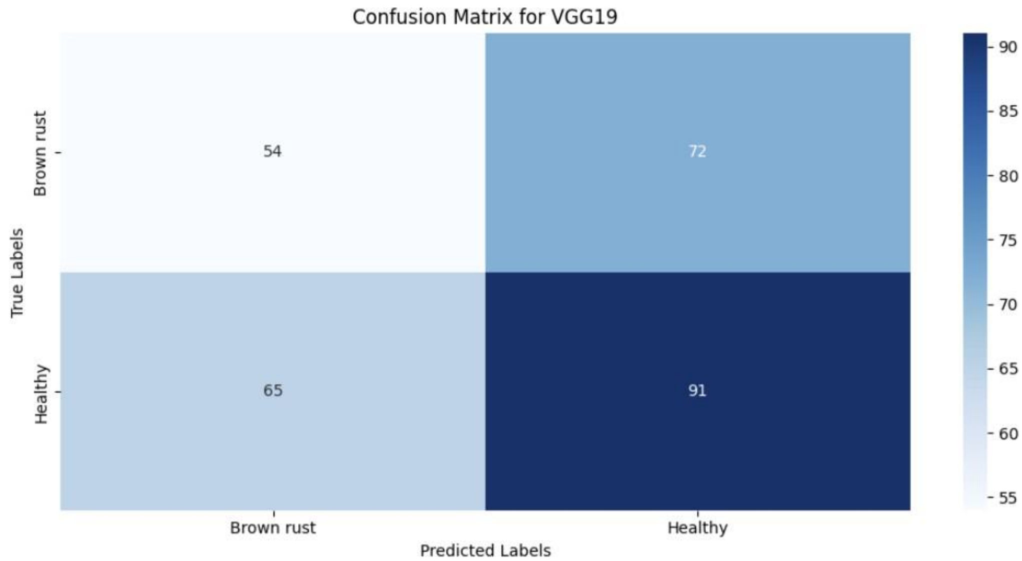

Figure 5.3.8: Confusion Matrix of VGG19

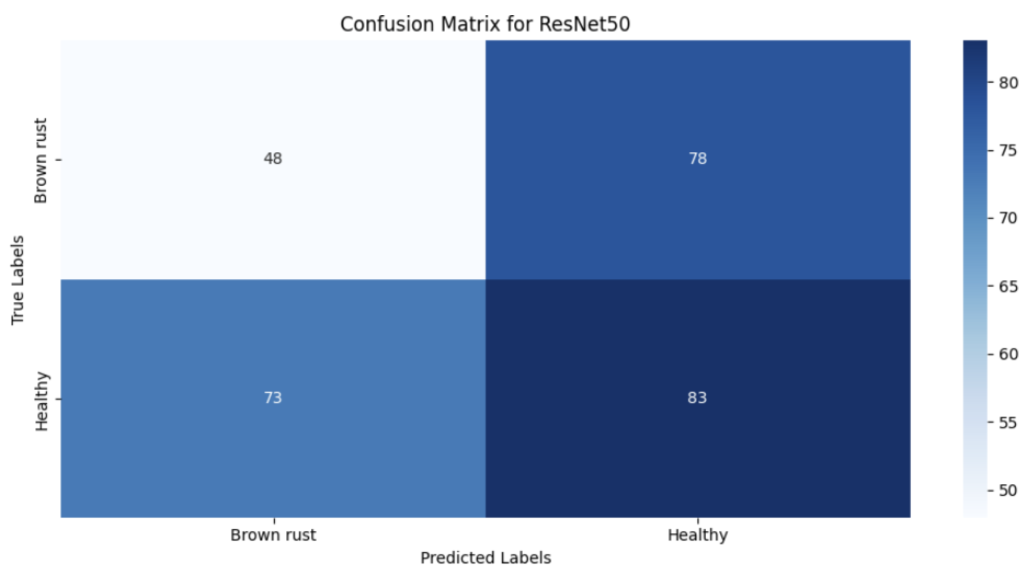

Figure 5.3.9: Confusion Matrix of RestNet50

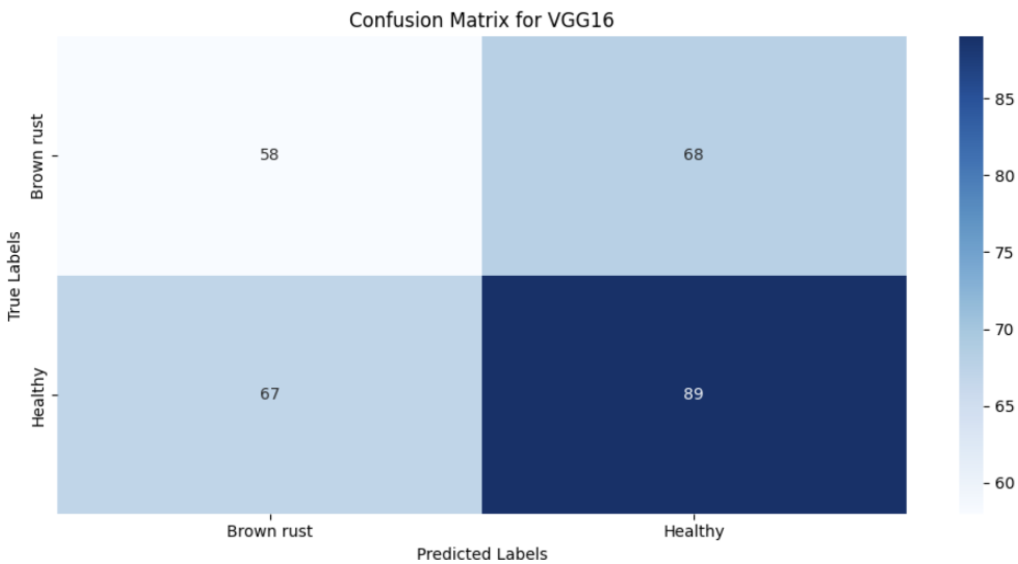

Figure 5.3.10: Confusion Matrix of VGG16

5.4 Summary

This study develops a real-time system for detecting wheat leaf diseases using computer vision on mobile devices. It evaluates five CNN models—EfficientNet, DenseNet, VGG19, ResNet50, and VGG16—for their ability to classify diseases, highlighting EfficientNet and DenseNet as top performers with 91% accuracy. Transfer learning is crucial in adapting these models for mobile use, balancing accuracy and efficiency. Detailed metrics, including loss graphs, confusion matrices, and precision-recall scores, validate the system's performance. The research demonstrates the potential of integrating advanced deep learning into portable disease detection tools for agriculture.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Automated solutions for detecting diseases in wheat leaves optimize operations by minimizing the need for manual work typically involved in identifying diseases. By reallocating agricultural laborers to more specialized professions, employment satisfaction among them can be enhanced. Implementing automation for repetitive operations in the agriculture industry improves workplace safety by minimizing occupational dangers and promotes the overall quality of life for workers.

6.2 Impact on Society & Environment

Society benefits from automated disease detection systems because they guarantee a steady supply of high-quality wheat, which increases food security and satisfies consumer demands. Economic stability is fostered by this dependability in agricultural communities. From an ecological perspective, these systems lessen the impact of farming on the environment by maximizing the use of resources and decreasing their waste, which in turn helps with inventory management.

6.3 Ethical Aspects

The possible effect on agricultural employment is one ethical consideration in adopting automated disease detection systems. Although automation has the potential to eliminate some jobs, it also offers chances for workers to improve their skills and be assigned more skilled jobs, which can help create a more fair transition. To solve these moral problems, we need policies that promote both technical progress and workers' personal and professional development.

6.4 Sustainability Plan

An effective strategy for implementing automated wheat leaf disease detection systems requires ongoing advancements in both technology and operations. This encompasses continuous research and development efforts aimed at improving the precision and effectiveness of the system, as well as proactive involvement with stakeholders to tackle emerging societal and environmental issues. Ensuring transparency in operations and strict adherence to sustainable practices are crucial for ensuring that these systems make a positive contribution to long-term sustainability goals while limiting negative consequences on the environment and society. Furthermore, utilizing energy-efficient gear and advocating for appropriate utilization of the technology might additionally contribute to environmental initiatives.

6.5 Summary

To summarize, automated methods for detecting diseases in wheat leaves are a significant advancement in agricultural technology, providing considerable advantages in various aspects of society, the environment, and sustainability. These systems have the potential to enhance the entire quality of life for agricultural communities by increasing productivity, managing diseases, and enhancing resource efficiency. Nevertheless, the use of these technologies requires thorough examination of ethical consequences and comprehensive sustainability strategies to optimize advantages while minimizing possible drawbacks. Adopting these technologies in a careful and deliberate manner can lead to a more effective, environmentally friendly, and adaptable agricultural system for future generations.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This work focuses on the creation of an innovative approach for promptly identifying and controlling diseases in wheat leaves. It harnesses the capabilities of deep learning and takes advantage of the widespread availability of modern computing systems. By using the enhanced computational powers of convolutional neural networks (CNNs), the system automates the process of identifying diseases, thereby decreasing thereliance on human involvement and mitigating errors caused by human prejudice. Thesystem's architecture enables its implementation in various agricultural environments, hence ensuring its availability to a wide spectrum of users across the agricultural supplychain.

The study assesses the efficacy of five well-known CNN models, namely EfficientNet, DenseNet, VGG19, ResNet50, and VGG16, in accurately diagnosing different types of illnesses affecting wheat leaves. By utilizing a dataset consisting of 2922 authentic photographs, sophisticated augmentation techniques are employed to increase the variety of the dataset, resulting in the creation of several images for each shot. EfficientNet and DenseNet have demonstrated exceptional performance, reaching impressive accuracy rates. This is supported by comprehensive metrics including training and validation loss graphs, confusion matrices, precision, recall, F1-score, and support for each class. The study emphasizes the importance of transfer learning methodologies, showcasing different patterns of performance across the assessed architectures. This study offers valuable insights into utilizing deep learning for automated identification of diseases in wheat leaves, paving the way for further improvement and practical use in agricultural technology.

7.2 Further Suggested Works

In order to improve the effectiveness and precision of identifying wheat diseases in real-time, it is crucial to make substantial progress in optimizing algorithms and utilizing hardware efficiently. To ensure the detection system's robustness and adaptability, it is necessary to continuously expand the dataset by include a wide rangeof wheat types from different places and seasons. Moreover, the task of adapting the wheat disease detection system to handle extensive wheat fields is a significant obstaclethat requires the creation of inventive approaches and scalable remedies.

The exploration of integration possibilities amongst agricultural machinery, such as drones, robotic sprayers, and autonomous field monitoring systems, has the potential to completely transform precision agriculture. The purpose of this integration is to enhance the efficiency of the detection process and streamline the coordination among various components of the agricultural ecosystem. Furthermore, it is imperative to create a more intuitive and user-friendly interface for the mobile or web-based application. An interface of this nature would facilitate seamless interaction between farmers and agricultural workers with the disease detection system, hence improving its usability and adoption.

Furthermore, incorporating other characteristics such as comprehensive disease management suggestions and linking with agricultural databases to provide current treatment instructions will greatly enhance the effectiveness and convenience of use of the system. The significance of enhanced technological integration in modern agriculture is further highlighted by the emphasis on real-time detection capabilities for detecting disease severity. Together, these endeavors strive to establish an all-encompassing and advanced disease detection system that caters to the diverse requirements of modern agricultural techniques.

7.3 Limitations

Although there is promise for breakthroughs in wheat disease detection systems, it is important to highlight the presence of several restrictions and conflicts of interest. A major constraint is the high processing resources needed to achieve real-time performance on mobile or edge devices. Attaining rapid and precise detection may need sophisticated machinery, which could be financially impractical for numerous farmers, particularly in underdeveloped areas. Moreover, the ongoing enlargement of the dataset to encompass a broader range of wheat diseases and climatic circumstances poses difficulties concerning the gathering, labeling, and retention of data. This approach requires a significant amount of resources and may not always provide a complete analysis due to the extensive variety of wheat species and growth circumstances.

Expanding the wheat disease detection system to cover extensive wheat fields involves more intricacies. Fluctuations in external factors, such as illumination and atmospheric conditions, might impact the precision of detection, therefore requiring resilient and flexible algorithms. Integrating the detection system with agricultural gear, such as drones and autonomous field monitoring systems, may provide technical and logistical difficulties. These problems include assuring compatibility and handling the substantial investment needed for these technologies. In addition, creating a user-friendly interface for the program, although crucial, may not completely cater to the diverse degrees of technological proficiency among farmers and agricultural laborers. Incorporating elements such as comprehensive illness management suggestions, although advantageous, may complicate the interface and necessitate further training for optimal utilization. Conflicts of interest may occur if the creation and implementation of the wheat disease detection system are influenced by commercial motives, perhaps favoring profitability over accessibility and fairness. It is essential to prioritize ethical norms and inclusive agricultural development by ensuring that technology serves a wide range of users, rather than solely focusing on major agricultural operations.

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Appendix A

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

Title: AUTOMATED WHEAT LEAF QUALITY ASSESSMENT THROUGHCOMPUTER VISION AND DEEP LEARNING

Students ID: 203-15-14462, 203-15-14468

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**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 the 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 demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting advanced CNN architectures.	**Page no:** [22-25] **Section:** [3.2.3]
				After completing different components types of integration, we will design an android application that covers **K5 and K6**	**Page no:** [26-27] **Section:** [3.2.4]
				We have studied existing works with similar goals which address the knowledge profile **K8**	**Page no:** [7-12] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	Despite advancements, challenges remain in the development automated wheat leaf grading systems.Issues such as variability in wheat leaf appearance, environmental conditions, and hardware constraints pose significant hurdles to overcome.	**Page no:** [3] **Section:** [1.5]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Navigating our project landscape proved challenging, notably due to the scarcity of research on similar wheat leaf quality detection systems utilizing Android phones. With limited prior work to draw upon, we embarked on an extensive analysis to identify and adapt suitable algorithms, aiming to pioneer advancements in this under explored domain.	**Page no:** [38-47] **Section:** [5.2, 5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO3	We encountered a notable gap in research within this domain. Few studies have delved into the intricacies of developing such systems. Particularly, we faced the challenge of determining effective methodologies to measure and assess wheat leaf quality attributes using smartphone technology, requiring innovative approaches and careful consideration of various factors.	**Page no:** [12-13] **Section:** [2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders and involved**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO3	This project comprises several subsystems that depend on each other. These include tasks such as collecting data, processing it, training machine learning models, conducting predictive analysis, and developing a front-end application.	**Page no:** [15-23] **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		Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in wheat leafs quality detection through computer vision.	**Page no:** [27,30] **Section:** [3.3, 3.4]
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		This project contributes to society by ensuring the delivery of high-quality, disease-free wheat leaf through advanced deep learning detection methods. It promotes environmental sustainability by reducing food waste, optimizing resource usage, and lowering the carbon footprint. By leveraging efficient computational resources and adhering to ethical guidelines, the project supports both consumer health and the economic well-being of farmers.	**Page no:** [48-49] **Section:** [6.3, 6.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in wheat leaf quality assessments through computer vision, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7, 12] **Section:** [2.2, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project meets CO4 by incorporating robust project management and financial oversight strategies. It ensures thorough planning, precise resource allocation, and accurate budget estimation, leading to optimal utilization of resources throughout the research lifecycle.	**Page no:** [27, 30] **Section:** [3.3, 3.4]
2	CO9	Yes	The project upholds ethical principles by ensuring the privacy of data, obtaining necessary consents, and transparently documenting the research process. This	**Page no:** [49]

			approach guarantees responsible dissemination of knowledge and promotes societal well-being through the ethical application of advanced technologies for wheat leaf diseases assessment, fully complying with CO9.	**Section:** [6.3]
3	CO10	Yes	Me and team member equally worked	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [15-47] **Section:** [3.2, 4.2, 5.2,5.3]

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