**Wheat Rust Guard**

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**Spring/Fall 2024-2025**

**A Dissertation Submitted To**

**Faculty of Computing,**

**Riphah International University, Islamabad**

**As a Partial Fulfillment of the Requirement for the Award of the Degree of**

**Bachelors of Science in Computer Science**

**Faculty of Computing**

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**Final Approval**

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**Declaration**

We hereby declare that this document “**Wheat Rust Guard**” neither as a whole nor as a part has been copied out from any source. It is further declared that we have done this project with the accompanied report entirely on the basis of our personal efforts, under the proficient guidance of our teachers, especially our supervisor **Mr. Zeeshan Ali**. If any part of the system is proved to be copied out from any source or found to be reproduction of any project from anywhere else, we shall stand by the consequences.

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**Dedication**

Our project is dedicated to our parents, seniors, friends and our supervisor “Mr. Zeeshan Ali” for their insightful guidance and patience throughout this journey. I also extend my gratitude to my friends and peers for their camaraderie and encouragement, which kept me motivated. Finally, I dedicate this work to everyone who inspired me to pursue excellence and to the pursuit of knowledge that continues to drive my aspirations.

**Acknowledgement**

First of all we are obliged to Allah Almighty the Merciful, the Beneficent and the source of all Knowledge, for granting us the courage and knowledge to complete this Project.

We owe a debt of gratitude to “Mr. Zeeshan Ali,” our project supervisor. Without their individual oversight, counsel, and invaluable direction, this project’s conclusion would have been questionable. We are incredibly grateful to them for their support and ongoing assistance throughout the project. We are also grateful to our parents and family, who have always supported us and taught us the importance of integrity and diligence.

**\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_**

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**Abstract**

Wheat rust is among the most important agricultural threats affecting agricultural productivity and food security worldwide. Traditional diagnosis of wheat rust consumption involves much time and inefficiency; most of the time, human error may cause interventions that might be belated by farmers. This project, Wheat Rust Guard, detects wheat rust diseases through automation using state-of-the-art artificial intelligence techniques. Computer vision and deep learning have been applied here to categorize wheat crops into Healthy, Yellow Rust-affected and Brown Rust-affected with the help of image-based analysis. Further, the application of this system has been integrated on a mobile device for the convenience and ease of farmers. The application shall provide instantaneous results regarding the condition of the crop, along with the treatment recommendations, and has the capability to function offline in areas where internet access is poor or no internet. This, in turn, results in a scalable, efficient, user-friendly tool that will enable farmers to undertake timely action and thereby improve the health of the crop, ensuring sustainable agriculture.

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# Abstract

The **Wheat Rust Guard** will provide the farmers community with an efficient, mobile-based platform for the detection and management of wheat rust diseases. The application will be made using **Flutter** and **Dart**,which will incorporate advance deep learning models in the detection of the diseases. It enables users to upload or scan images of wheat crops for the application of the identification process through AI-powered computer vision capable of identifying diseases like **Yellow Rust** and **Brown Rust**.

This contains a user-friendly interface that navigates farmers step by step. Onboarding is also designed to make usage easy for those who are not familiar with the technology. The app allows offline functionality in areas with low internet connectivity. Treatment recommendations will also be provided to help the farmer take timely and corrective action.

The app applies AI-driven analysis to guarantee high accuracy in detecting diseases of wheat rust, eliminating all inefficiencies that may characterize traditional manual diagnostics. But most importantly, Wheat Rust Guard empowers them with a scalable and efficient solution-meaning better crop health and truly sustainable agriculture.

# Introduction

Agriculture is the backbone of the economy in Pakistan and provides employment for day-to-day livelihood to millions. However, wheat rust-a highly destructive fungal diseases-seriously threatens wheat, the staple crop of the country. It affects the quality and quantity of the yield, causing losses in substantial economic earnings and imposing a hazard to food safety. Conventional diseases detection methods, however, are manual, which means time consumption, inaccuracies, and leaving farmers unprepared to take efficient actions against the disease accordingly.

Addressing these challenges, Wheat Rust Guard offers the integration of artificial intelligence and computer vision as a paradigm shift in wheat rust detection. The application enables farmers to detect wheat rust diseases – such as Brown Rust and Yellow Rust – by scanning or uploading images of affected crops. Advanced deep learning models applied within the app ensure a correct real-time diagnosis, while offering active insights to farmers for effective management.

The offline application of the system, other than detecting diseases, also suggests recommendations for treatment, hence making it accessible even in remote areas. Wheat Rust Guard propagates a junction between modern day technology and agricultural requirement in simplification of disease diagnosis and prevention, hence leading to sustainable farming and increasing crop yields.

## Goals and Objectives

The main goals and objectives of the Wheat Rust Guard project are:

1. Development of an AI-enabled mobile application that is capable of detecting wheat rust diseases, Brown Rust and Yellow Rust with high accuracy.
2. To provide effective, well-timed, and actionable insights to farmers for better disease management.
3. To implement user-friendly functionalities like offline access and treatment suggestions that could further improve the accessibility and usability.
4. To reduce the reliance on manual diagnostic methods, saving time and improving detection accuracy.
5. To contribute to environmentally friendly agriculture and to raise wheat production to achieve food security.

## Scope of the Project

The scope of Wheat Rust Guard will include:

1. Developing a mobile application using Flutter and Dart that employs AI and deep learning models.
2. It was aimed at the development of the capability to diagnose wheat rust diseases through uploading the image or scanning live.
3. Integration of added features such as offline mode and suggestion of treatment that help to solve the accessibility related to farmers.
4. The target would be small to medium scale farmers in Pakistan, particularly in less accessible parts of the country for access to agricultural equipment or modern farming technologies.
5. Scalability and flexibility ensure the detection of other crop diseases in the future.

# Literature Review

## Introduction

This chapter focuses on a review pertaining to present studies and developments about early identification studies using artificial intelligence powered with computer vision for specific wheat rust diseases, precisely yellow and brown rust. Specific state-of-the-art AI tools related to agriculture, methodologies presented concerning the disease detection phases involved in this research area and deficiencies of the current resolution in the literature are debated herewith. It lays the foundation for the understanding of how the Wheat Rust Guard project innovates on existing approaches by offering a mobile-based, user-friendly platform, catering to farmers.

## Background and Problem Elaboration

Wheat rust diseases are considered some of the most feared diseases that attack wheat all over the world. These fungal infections will degrade not only the crop yields but also the quality of grains, thus impacting food security as a whole and farmers livelihoods. Management of any such disease requires early detection of the disease so that at least its impact could be minimized.

Traditional monitoring methods for wheat rust rely on either a manual inspection or the expert opinion of agricultural personnel. While effective to a degree, there are a number of limitations in these approaches:

* **Inefficiency and Cost:** Manual inspection is very time-consuming, requiring much labor, especially on large fields.
* **Inaccessibility:** Most small-scale farmers in developing regions face the challenge of a lack of accessibility to professional advice and improved equipment.
* **Delayed Diagnosis:** By the time symptoms are visible, the diseases has probably spread so extensively.

These challenges have transformative solutions through advances in AI and machine learning. In agriculture-food, AI has appeared to be effective in precision tasks concerning disease detection, yield estimation and soil analysis. Computer vision, a subcategory of AI, has proven especially apt, through visual data analysis of symptoms for the detection and identification of diseases with much accuracy. However, most of these tools driven by AI are either too costly, or require technical capability, or are beyond the reach and access of small-scale farmers. The Wheat Rust Guard Project fills this gap by providing an inexpensive, mobile-based platform for the early detection of wheat rust. Equipped with AI and computer vision, this tool enables farmers to quickly identify infections and reduces time and effort spent in monitoring while improving decision-making and response times.

## Detailed Literature Review

### Definitions

The following definitions are relevant and provide a basic understanding for the basis of this project:

* **Artificial Intelligence:** It is the ability of machines, especially computer systems, to simulate processes of human intelligence and, therefore, be able to carry out tasks that require making decisions, learning, and solving problems. Machine learning – subcategory of AI engaged in the development of algorithms through which systems can learn and improve processes from experience without explicit instructions. This can handle ML models learning from labeled datasets to recognize signs of wheat rust.
* **Computer Vision:** This is a subfield of AI, where machines have the ability to interpret, analyze and process images or videos. In this context, computer vision algorithms in Wheat Rust Guard analyze images of wheat leaves for rust symptoms.
* **Precision Agriculture:** This is the application of technologies in managing farming practices by monitoring field variability to apply intervention where exactly it is required. The project epitomizes precision agriculture, whereby the use of AI tools on mobile devices in the targeted detection of diseases was considered.
* **Yellow Rust / Stripe Rust:** A fungal disease, happening due to puccinia striiformis on wheat leaves in forms of yellow stripes thus offering considerable yield loss.
* **Brown Rust / Leaf Rust:** It is a fungal disease because of the fungus puccinia triticina; it shows reddish-brown-colored spots on the leaves of wheat, and it reduces the photosynthetic capability along with physical strength.

### Related Research Work 1

Romain Bebronne et al.[1] proposed a methodology for detecting fungal diseases within winter wheat, specifically stripe rust (SR), brown rust (BR), and septoria tritici blotch (STB). The authors applied reflectance and textural features from multispectral imagery. Their system integrated a ground-based platform fitted with a multispectral camera that captured wavebands over the entire visible and near-infrared spectrum. They conducted the estimation of disease severity based on spectral and textural data using ANN and PLSR models. Major steps involved in preprocessing were the segmentation of multispectral images and waveband-specific feature extraction. ANN outperformed PLSR in predicting disease severity with \( R^2 \) values of 0.72, 0.57, and 0.65 for STB, SR, and BR, respectively. STB disease severity classification accuracy at higher infection thresholds was 81%. The study showcased the potential of integrating reflectance data with machine learning for precision disease monitoring under natural conditions of the field.

### Related Research Work 2

Mamatha Mandava et al.[2] investigated a few deep learning models for yellow rust detection in wheat due to \*Puccinia striiformis\*. These studies compared the performance of three CNN architectures, namely ResNet50, DenseNet121, and VGG19, using a dataset comprising annotated images of healthy/infected wheat leaves. These models were trained using well-known techniques of data augmentation and transfer learning to enhance their generalizability. ResNet50 and DenseNet121 were very efficient, while VGG19 had a moderate performance in feature extraction. EfficientNetB3 gave the best accuracy among the models compared in this work and is suitable for large-scale precision agriculture real-time monitoring. Advanced CNN-based systems have been underlined in this work that achieve high classification accuracy to help in early disease detection.

### Related Research Work 3

Habib Khan et al.[3] have proposed a framework for automatically classifying wheat diseases that uses ML, with special emphasis on the classification of yellow and brown rust diseases.

It proposes field data collection from different regions in Pakistan with strong preprocessing like image segmentation and resizing to retain high input quality. The proposed framework compared several ML algorithms based on the above approach and achieved the maximum accuracy of 99.8%, which was beyond the results of the conventional methods. They highlighted the importance of efficient preprocessing and data preparation in ML applications, showcasing the effectiveness in real-world settings with such diverse environmental conditions.

### Related Research Work 4

Wang et al.[4] described an image-processing-based stripe rust- and leaf rust-infected identifying system on the wheat varieties under different environmental conditions. Its approach flowed by taking a single-leaf image in high resolution, scaling, doing some morphological reconstructions, and extracting these various median filters and lesion segmentations, with segmentation extracted onto 140 color, text, and shape features. Further, feature selection was undertaken via Relief, 1R, and correlation-based feature selection along with PCA. The implementation had been done on SVMs, BPNN, and random forest for both single- and multi-variety identification using ML models.

Under greenhouse conditions, the multi-variety models had identification accuracies as high as 100%, thus demonstrating their potential to monitor disease with accuracy across diverse wheat varieties.

### Related Research Work 5

Shafi et al.[5] have developed an embedded AI for the classification of wheat yellow rust infection types, including healthy, resistant, moderately resistant, and susceptible.

They collected their dataset indigenously and preprocessed it using the U2-Net model for background removal. Two deep learning classifiers were implemented: ResNet-50 and Xception. The best performance, with accuracy as high as 96%, was achieved by ResNet-50. Further, the model deployed on the edge computing device enables real-time monitoring. Thus, farmers are able to detect the rust severity in situ out in the field. This research highlights how the embedding of AI with portable devices has enormous potential to improve precision agriculture and, therefore, management of crop health.

### Related Research Work 6

Cuenca-Romero et al.[6] addressed the issue of unbalanced datasets in the identification of yellow and brown rust in wheat using hyperspectral imaging and machine learning. They used the SMOTE algorithm for augmentation in their dataset and then trained ANN, SVM, RF, and GNB models. RF performed best for yellow rust detection, giving an accuracy of 70% on raw datasets, while SVM was the best for brown rust detection on augmented data.

This study applied the integration of information of spectral reflectance owing to its efficiency in executing early detection of diseases, incorporating an investigation of machine learning-model performance into the dataset imbalance problem toward reliable identification.

### Related Research Work 7

Nguyen et al.[7] proposed a new system for early detection of wheat yellow rust using multispectral UAV imagery. Their approach combined VIs and GLCM texture features to capture the spectral and spatial dimensions of disease progress. They used a 3D-CNN for disease monitoring, which achieved detection accuracies of 60% at the early tillering stage up to 79% at flowering stages. Critical spectral bands included the red-edge (690-740 nm) and near-infrared (740-1000 nm) regions, which were key for disease differentiation.

In that sense, this approach showed that through an early detection method, 3-7% of crop yield could be conserved, which would correspondingly create added value for precision agriculture economically viable.

### Related Research Work 8

Liu et al.[8] presented StripeRust-Pocket, a smartphone-based deep learning app used in measuring stripe rust severity of wheat. The segmentation of a two-stage model in the system was realized using StripeRustNet, which combines MobileNetV2-DeepLabV3+ for leaf segmentation with ResNet50-DeepLabV3+ for lesion segmentation.

It was able to achieve 98.65% mean intersection over union for segmenting a leaf and 86.08% for lesion segmentations. Moreover, by using a custom labeling pipeline, the time spent annotating reduced from 20 minutes to 3 minutes per image. Also, on-site disease monitoring is made possible with the mobile application, letting the researcher and farmer have an easy implementable tool for timely treatment of the disease.

### Related Research Work 9

Alharbi et al.[9] The model suggested here for the classification of wheat disease through few-shot learning combined the concept of EfficientNet along with the attention mechanism for feature selection. The developed technique provided excellent results on 18 classes of wheat diseases with highly limited training data, which proved to yield 93.19% accuracy on custom images and 98.5% accuracy on the CGIAR dataset. This work tries to address the challenge of data availability and catastrophic forgetting using continual learning, hence showing its prospect in efficient disease identification in resource-constrained environments.

### Related Research Work 10

Kumar and Kukreja[10] designed a hybrid model, combining a generative adversarial network-STARGAN-with a convolutional neural network-CNN-for wheat yellow rust classification. Here, the STARGAN model was used for augmenting the data, while CNN was trained for multi-level severity detection. Their model had attained 95.6% accuracy at medium severity levels and outperformed some other deep learning models like a fully convolutional network and random forests.

The study also highlighted hybrid models as essential in improving the accuracy of disease prediction when conditions are unfavorable.

### Related Research Work 11

Tolba and Talal[11] proposed the Mobile-DNN-Net model, a hybrid of deep learning models combined taking the most important features from both feature extractors, namely MobilNet and DCNN. Recently, early detection and classification of diseases on wheat leaves with gradual class activation maps provided substantial explainability. Works also have been validated over different datasets of high-resolution images given a total of 15 classes of diseases that represented 14,155 images totally. Mobile-DNN-Net ensured better accuracy and more ex-plainability when using other compared models and makes robust tools within precision agriculture.

### Related Research Work 12

Jiang et al.[12] made a comparative assessment of the performance of VGG-16, Inception-v3, ResNet-50, and other architectures for wheat leaf disease using field-acquired photographs. "Transfer learning" approach adopted for the models with appropriate hyper-parameter tuning on Field-based Wheat Diseases Images-FWDI custom dataset. Among these models, the performance achieved varied from Inception-v3, the top among them with an accuracy of 92.5%, while MobileNetV3 showed the fastest process with poorer accuracy. It reflected how model architecture, training strategy, and input data quality interact in the process of diagnosing diseases.

## Literature Review Summary Table

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Name** | **Reference** | **Year** | **Input** | **Output** | **Description** |
| Romain Bebronne et al. | [1] | 2020 | Multispectral imagery (visible & NIR). | Disease severity R^2: STB (0.72), SR (0.57),BR (0.65); STB threshold classification (81%). | Methodology integrating reflectance and textural data with ANN / PLSR for fungal disease severity detection. |
| Mamatha Mandava et al. | [2] | 2024 | Annotated wheat leaf images. | EfficientNetB3 had the best accuracy. | Compared CNN models (ResNet50, DenseNet121, VGG19, EfficientNetB3) for yellow rust detection. |
| Habib khan et al. | [3] | 2022 | Field-collected wheat leaf images. | Classification accuracy of 99.8%. | ML models with segmentation and resizing; focused on yellow and brown rust classification. |
| Wang et al. | [4] | 2023 | High-resolution single-leaf images. | 100% accuracy (greenhouse conditions). | Feature selection (Relief, PCA) and ML models for rust detection across multiple wheat varieties. |
| Shafi et al. | [5] | 2023 | Indigenously collected images. | ResNet-50: 96% accuracy. | Edge AI for real-time monitoring; background removal with U2-Net. |
| Cuenca- Romero et al. | [6] | 2024 | Hyperspectral imaging. | RF: 70% for yellow rust; SYM: best for brown rust. | Addressed dataset imbalance using SMOTE; focused on spectral reflectance for early detection. |
| Nguyen et al. | [7] | 2023 | UAV multispectral imagery. | Detection: 60% (early), 79% (flowering). | 3D-CNN using VI and GLCM texture features for yellow rust monitoring; conserved crop yield (3-7%). |
| Liu et al. | [8] | 2024 | Smartphone images. | Leaf segmentation: 98.65%; lesions: 86.08%. | Developed StripeRust-Pocket app; reduced annotation time; enabled on-site rust monitoring. |
| Alharbi et al. | [9] | 2023 | Few-shot learning with CGIAR dataset. | 93.19% (custom), 98.5% (CGIAR dataset). | Combined EfficientNet with attention mechanism for wheat disease detection under data-constrained scenarios. |
| Kumar & Kukreja | [10] | 2023 | Augmented wheat leaf images. | 95.6% accuracy at medium severity levels. | Hybrid STARGAN-CNN model for wheat yellow rust detection. |
| Tolba et al. | [11] | 2024 | High resolution wheat leaf images. | High accuracy across 15 classes. | Mobile-DNN-Net combining MobilNet and DCNN for early disease classification and explainability. |
| Jiang et al. | [12] | 2022 | Field acquired wheat leaf photographs. | Inception-v3: 92.5% accuracy. | Transfer learning for wheat disease detection using multiple CNN architectures. |

## Research Gap

Despite significant advancements in wheat disease detection using multispectral imagery, machine learning (ML), and deep learning (DL) techniques, several challenges persist:

* **Early Detection at Subtle Stages**: Many studies, such as Nguyen et al.[7] and Romain Bebronne et al.[1], showed limited accuracy for early-stage disease detection (e.g., Nguyen et al.: 60% accuracy at tillering stage). There is a need to enhance the sensitivity of models for early disease progression stages.
* **Generalization Across Environments**: Most works, such as Habib Khan et al[3]. and Wang et al.[4], are region-specific and tested under controlled conditions (e.g., greenhouse). However, wheat diseases exhibit variability due to environmental, regional, and genetic differences. Research must focus on robust systems applicable across diverse regions and natural conditions.
* **Data Scarcity and Imbalance**: Studies like Cuenca-Romero et al[6]. have addressed dataset imbalance using SMOTE, but real-world datasets remain scarce and unbalanced, especially for rare disease cases. Techniques such as few-shot learning, continual learning, and synthetic data generation require further exploration.
* **Integration with Real-Time Monitoring Systems**: Although advancements like StripeRust-Pocket and Shafi et al.'s[5] edge AI offer real-time solutions, they often lack scalability for large farms or regions with poor infrastructure. Further work is required to improve computational efficiency and accessibility of such technologies.
* **Explainability and Transparency**: While Tolba et al[11]. explored class activation maps for explainability, the majority of DL approaches remain black-box models. There is a pressing need for interpretable AI models to enhance farmer trust and practical usability.
* **Integration of Multimodal Data**: Studies primarily focused on single modalities (e.g., hyperspectral or visual imagery). Future research can explore the fusion of multiple data types, such as thermal imagery, environmental data, and soil health, to improve disease prediction accuracy and reliability.
* **Economic and Environmental Viability**: Limited attention has been given to cost-effective and environmentally sustainable disease monitoring solutions for smallholder farmers. Technologies must address these aspects to ensure broader adoption.

These gaps underline the necessity for more comprehensive, scalable, and interpretable solutions in precision agriculture for wheat disease monitoring and management.

## Problem Statement

Wheat rust diseases, particularly yellow and brown rust, pose a significant threat to wheat crops in Pakistan, leading to reduced yields and economic losses. In Pakistan majority of fields in Tando Allahyar, Sindh were affected by leaf rust, whereas Chakwal, Punjab was mostly impacted by yellow rust.

Current diagnostic methods face several key challenges, including the variation in lesion scale, where disease symptoms appear in different sizes and shapes on infected wheat leaves, complicating the accurate identification of the region of interest (RoI). Additionally, varying lighting conditions in real-world field environments make it difficult for models to consistently detect disease features. While deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in plant disease classification, their complexity leads to long training times, high computational costs, and a requirement for large and diverse datasets, which are often not available. These factors hinder the real-time application of such models in the field. There is a need for an efficient and accurate wheat disease diagnosis system that can overcome these limitations by incorporating different feature extraction, adapting to lighting variations, and reducing the training complexity of deep models. This project aims to develop such a framework, delivering a solution that provides real-time, precise detection of wheat rust diseases while minimizing environmental impact through reduced pesticide misuse.

# Requirements and Design

The Wheat Rust Guard is a mobile based platform that was developed to support farmers in the early detection of wheat rust diseases, such as Yellow Rust and Brown Rust, by applying advanced AI and computer vision techniques. This platform will be user-friendly, very easy to use and will provide convenience and efficiency for farmers and administrators who interact with this system.

## Requirements

### Functional Requirements

* **User / Farmer:**

Table ‑ Functional Requirements for Farmer

|  |  |
| --- | --- |
| **ID** | **Requirements** |
| FR-1.1 | User shall be able to sign Up. |
| FR-1.2 | User shall be able to login. |
| FR-1.3 | User shall be able to create profile. |
| FR-1.4 | User shall be able to edit profile. |
| FR-1.5 | User shall be able to recover password. |
| FR-1.6 | User shall be able to capture / upload image for detection of disease. |
| FR-1.7 | User shall be able to receive disease detection results. |
| FR-1.8 | User shall be able to receive treatment suggestions. |
| FR-1.9 | User shall be able to give feedback on treatment suggestion. |
| FR-1.10 | User shall be able to view history of disease detection and treatment. |
| FR-1.11 | User shall be able to perform offline functionality. |

* **Admin:**

Table ‑ Functional Requirements for Admin

|  |  |
| --- | --- |
| **ID** | **Requirements** |
| FR-2.1 | Admin shall be able to login to the system. |
| FR-2.2 | Admin shall be able to manage AI model integration. |
| FR-2.3 | Admin shall be able to monitor system usage such as active users, images uploaded and disease detections made. |
| FR-2.4 | Admin shall be able to manage user accounts. |
| FR-2.5 | Admin shall be able to manage treatment recommendations. |
| FR-2.6 | Admin shall be able to access dashboard. |
| FR-2.7 | Admin shall be able to generate reports. |
| FR-2.8 | Admin shall be able to monitor and troubleshoot errors. |
| FR-2.9 | Admin shall be able to backup and restore data. |

### Non-Functional Requirements

* **User-Friendly Interface:** The User-Interface of the system is very simple and user-friendly, allowing users to navigate easily and access the desired features without any confusion.

### Hardware and Software Requirements

## Proposed Methodology

### Overview

Our system Wheat Rust Guard aims to detect and classify wheat rust diseases by leveraging a mobile application integrated with deep learning model. The approach provides a user-friendly solution for users / farmers to identify the wheat rust disease effectively.

### Step-by-Step Process

* **Data Collection:** Firstly, we collected dataset of Wheat Rust such as Yellow Rust, Brown Rust and Healthy from online source such as kaggle.
* **Data Preprocessing:** This process involves removal of noise, cleaning data and resize dataset to cubic interpolation 224x224x3, also enhance the images quality for better applying deep learning model.
* **Data Augmentation:** It is applied to artificially increase the size and diversity of the dataset, which helps to prevent overfitting and improve the model’s ability to generalize to unseen images. Data augmentation enhances the model’s robustness and accuracy in classifying wheat leaf diseases.
* **Model Selection:** Choose an appropriate convolutional neural network (CNN) architecture for image classification, such as hybrid model to increase the accuracy and correctly identify the disease.
* **Model Training and Evaluation:** Train the selected CNN model using preprocessed dataset. Separate the dataset into train, test and validation with the ratio of 70%, 20% and 10% respectively. The evaluation of model is done through confusion matrix of that architecture on which the selected hybrid model is implemented.
* **Integration:** Developing a mobile app using flutter dart for front end, ensuring an intuitive user interface for users / farmers. Secondly we implement our backend using tensor-flow lite to integrate our hybrid model with our app, enabling automated wheat rust diseases detection and diagnosis based on uploaded images or scanned images because our system will also detect real-time scenario of wheat rust.
* **Testing and Validation:** Conduct thorough testing and validation of our system to ensure its accuracy and reliability by going on-field testing of wheat rust diseases and training our dataset on different CNN architectures to ensure best performing model. It is mandatory to evaluate the confusion matrix in order to check for the best CNN model.

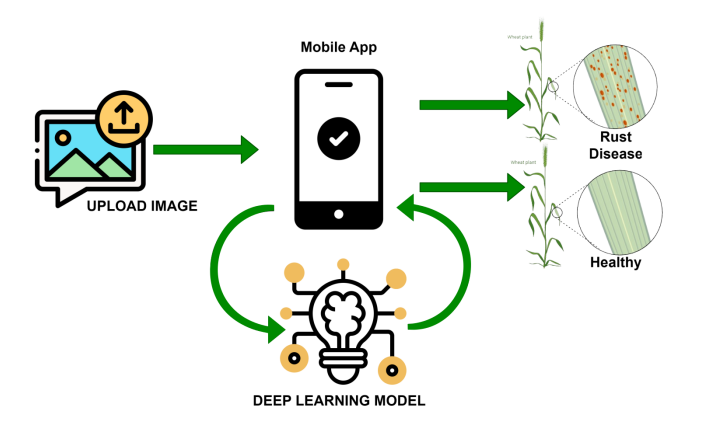


Figure ‑ Proposed Solution Diagram

## System Architecture

The major components in the system architecture of the project are three in number and include Image Input, a Mobile Application, and Deep Learning Model Integration. These will classify the wheat rust diseases namely Yellow Rust and Brown Rust. The workflow is as follows:

* **Image Input:** In the interface of the mobile application, the user can upload an image of a corn leaf, which will be the input to the system for its processing and classification.
* **Mobile Application:** The mobile application provides the basic interface to the user. It receives the uploaded image and talks to the deep learning model. The app should be developed in such a way that it presents a very friendly user experience whereby communications between the user and the model can be as smooth as possible.
* **Deep learning model:** In this model, the hybrid CNN analyzes an uploaded image. Then it processes and classifies this image into three major groups, namely Wheat Rust, Brown Rust and Healthy, returning the processed result to the mobile phone application.
* **Output Results:** The results from classification, along with confirmation through visual means and, if possible, type of disease, are reflected in the mobile application. Moreover, the output from this system is in such a format that even a person with no technical knowledge about diseases can understand. The modular architecture ensures that the system provides real-time disease detection, smooth workflow, and classifies the findings with a high degree of accuracy based on deep learning.

## Use Cases

* **User / Farmer:**

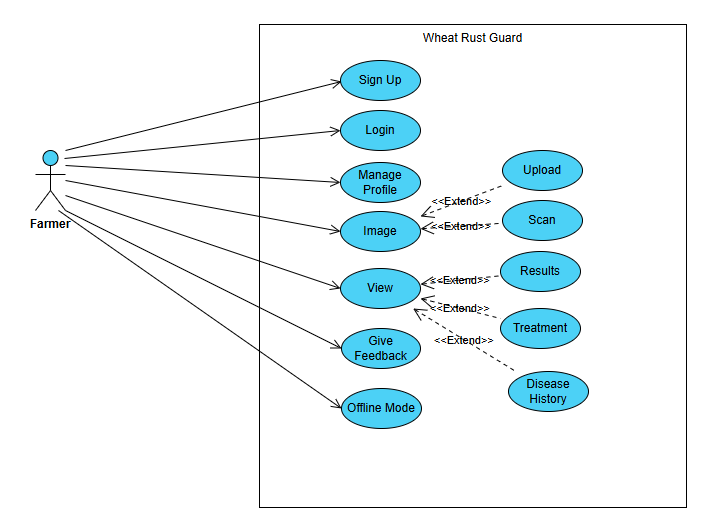


Figure ‑ Use Case Diagram for Farmer

* **Admin:**

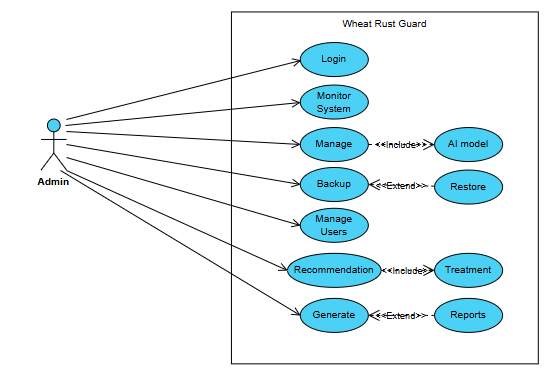


Figure ‑ Use Case Diagram for Admin

* **Complete Use Case Diagram:**

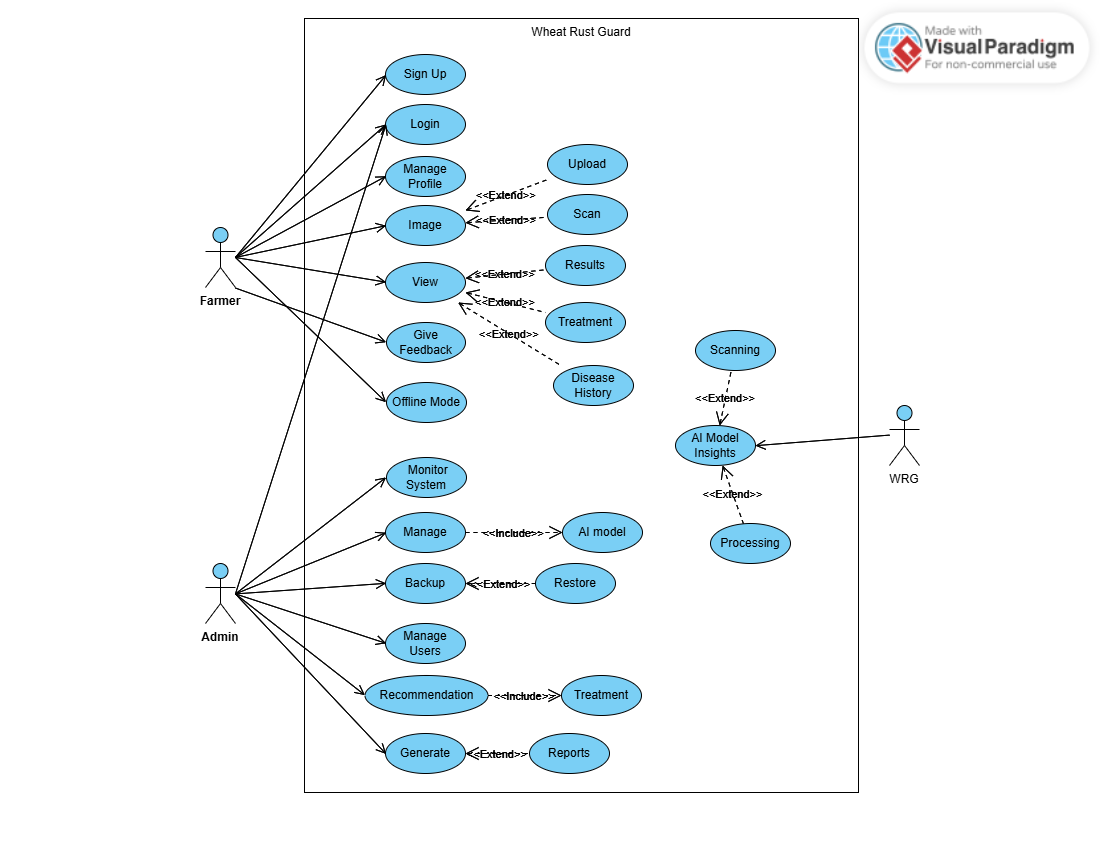


Figure ‑ Complete Use Case Diagram

### Fully Dressed Use Case

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Name | | Sample Use Case Name Here | | |
| Actors | | Admin, Business Owner, Store Manager | | |
| Summary | | The user shall provide their email and password on the login form and after successful verification, redirect the user to the home page. | | |
| Pre-Conditions | | The user must be in the database records either added by any of the authorized users or added manually by a developer.  The user must not already be logged in. | | |
| Post-Conditions | | The user’s session is successfully established and shall be redirected to the home page. | | |
| Special Requirements | | None | | |
| Basic Flow | | | | |
| Actor Action | | | **System Response** | |
| 1 | The user opens the login page. | | 2 | The login page is displayed asking for email and password. |
| 3 | The user enters valid email and password. | | 4 | The system verifies the email and password, establishes a session for the user and redirects the user to the home page. |
| **Alternative Flow** | | | | |
| 3 | The user enters invalid email or password. | | 4-A | The system responds with an error message: *Incorrect email or password entered.* |

## Database Design *(Optional)*

## Class Diagram (*Optional)*

## Sequence diagram *(Optional)*

## Any Other Artifact…

## GUI Graphical User Interfaces (*Optional)*

This section should give the GUI dumps of each screen, with reference to the user. The navigation flow of each user is also required, and each GUI should mark the functionality/use case that it covers.

# Implementation and Test Cases

## Implementation

This chapter details the steps involved in implementing the proposed wheat disease detection system using (methodology/technology). It covers the model selection, confusion matrix and performance assessment.

### Model Performance Analysis: MobileNet with Relu Activation

The model used the RELU (Rectified Linear Unit) activation function in its convolutional layers to introduce non-linearity and enhance feature learning. The following results were obtained during evaluation:

**Confusion Matrix:**

The confusion matrix provides insights into the model’s predictions across the three categories:

Table ‑ Performance Assessment MobileNet-Relu

|  |  |  |  |
| --- | --- | --- | --- |
| Actual / Predicted | Brown Rust | Healthy | Yellow Rust |
| Brown Rust | 183 | 12 | 1 |
| Healthy | 6 | 191 | 0 |
| Yellow Rust | 52 | 58 | 91 |

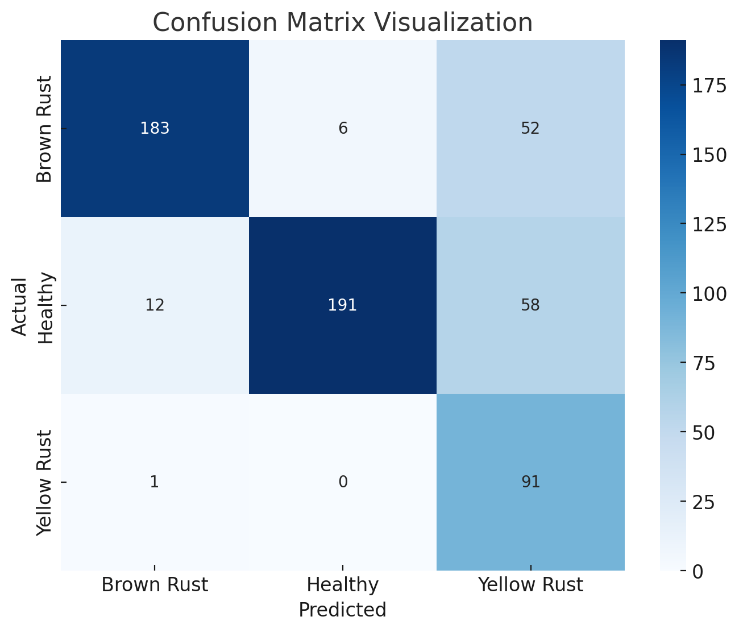


Figure ‑ Confusion Matrix MobileNet-Relu

From the confusion matrix:

* Brown Rust was correctly identified in 183 cases, with 12 misclassified as Healthy and 1 as Yellow Rust.
* Healthy images achieved high precision with only 6 misclassifications as Brown Rust and none as Yellow Rust.
* Yellow Rust faced challenges, with only 91 correct predictions and 52 misclassified as Brown Rust and 58 as Healthy.

**Performance Evaluation:**

Table ‑ Performance Evaluation MobileNet-Relu

|  |  |  |  |
| --- | --- | --- | --- |
| **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| 82.79 | 78.28 | 76.31 | 78.28 |

### Model Performance Analysis: MobileNet with Swish Activation

The MobileNet model with the Swish activation was utilized to enhance non-linearity and improve gradient flow during training, thereby improving the learning process. The evaluation results are as follow:

Confusion Matrix:

The confusion matrix demonstrates the model’s classification performance across three categories:

Table ‑ Performance Assessment MobileNet-Swish

|  |  |  |  |
| --- | --- | --- | --- |
| Actual / Predicted | Brown Rust | Healthy | Yellow Rust |
| Brown Rust | 145 | 36 | 15 |
| Healthy | 2 | 189 | 6 |
| Yellow Rust | 8 | 29 | 164 |

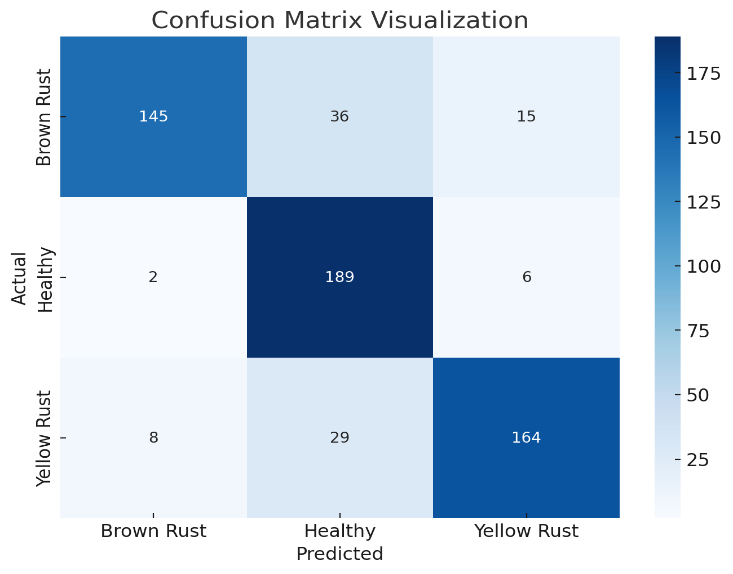
****

Figure ‑ Confusion Matrix MobileNet-Swish

Observations:

* **Brown Rust**: Correctly classified 145 instances, with 36 images misclassified as Healthy and 15 as Yellow Rust.
* **Healthy**: Achieved strong performance, correctly identifying 189 cases, with only 2 misclassified as Brown Rust and 6 as Yellow Rust.
* Yellow Rust: The model performed well in this category, correctly predicting 164 cases, but with 8 misclassifications as Brown Rust and 29 as Healthy.

Performance Evaluation:

Table ‑ Performance Evaluation MobileNet-Swish

|  |  |  |  |
| --- | --- | --- | --- |
| **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| 85.54 | 83.83 | 83.81 | 83.83 |

## **Test case Design and description**

**This section will be added in FYP-II.** Summarize the common attributes of test cases. This may include input constraints that must be true for every input in the set of associated test cases, any shared environmental needs, any shared special procedural requirements, and any shared case dependencies. The following scheme is recommended for describing test cases in detail.

### Sample Test case No.1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **<Software component Name>** | | | | | |
| **<Reference>** | | | | | |
| Test Case ID: | | *Reference Number* | Test Date: | | *Date* |
| Test case Version: | | *Version number* | Use Case Reference(s): | | *Relation to use cases* |
| Revision History: | | *Refer to previous test case identity (if any)* | | | |
| Objective | | *Need and scope of the testing* | | | |
| Product/Ver/Module: | | *Refer to overall system being built and the place of this test case in it.* | | | |
| Environment: | | *Necessary and desired properties of the test environment. (hardware/software)* | | | |
| Assumptions: | | *Assumptions that might affect the testing process.* | | | |
| Pre-Requisite: | | *Necessary condition that needs to be fulfilled prior to the test case.* | | | |
| Step No. | Execution description | | | Procedure result | |
|  | *Events being tested.* | | | *Mention software response.* | |
| Comments: | | | | | |
| *Passed* *Failed* *Not Executed* | | | | | |

### Sample Test case No.2

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## Test Metrics

Summarize here the common ground of attributes of test case metrics.

### Sample Test case Matric.No.1

|  |  |
| --- | --- |
| Metric: | Purpose |
| Number of Test Cases: | Total number of test cases that you have developed for your system. |
| Number of Test Cases Passed: | The number of test cases that successfully passed |
| Number of Test Cases Failed: | The number of test cases that failed |
| Test Case Defect Density: | (No of test cases failed \* 100)  No of test cases executed |
| Test Case Effectiveness: | No of defects detected using test cases \*100  Total number of defects detected |
| Traceability Matrix: | Traceability is the ability to determine that each feature has a source in requirements and each requirement has a corresponding implemented feature. |

### Sample Test case Metric.No.2

### Sample Test case Metric.No.3

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# Experimental Results and Analysis

**This chapter will be added in FYP-II.** Give proper analysis and discussion of experimental results (in plain English text) along with tables of results. **For each chapter provide a paragraph of introduction and in the end a paragraph of conclusions.**

# Conclusion and Future Directions

**This chapter is mandatory.** Give conclusions and summary of the work done. What were your findings and what were the results? Discuss in detail whether the scope of your project was entirely covered or not and whether the objectives of the project were met or not. What challenges did you face and what has been left out and why?

Sum up all the conclusions of all the chapters here to make a conclusion chapter. Do not repeat any text, just summarize it in different words.

Give recommendations for future work also. How your project can be further enhanced or improved? Future recommendations if someone wants to work on it. **For FYP-1 it is mandatory to list down a plan of the work to be done for FYP-2.**

**Future Work for FYP Part-II:**

* Enrich the dataset by including an "unknown" class with pictures of leaves from other than wheat but looking similar to the wheat leaves.
* Diversify the data collection for the unknown class in order to improve model robustness.
* Make the application interface more friendly and accessible to farmers.
* Employ deep learning to optimize the model in such a way that it enhances the accuracy of disease detection.
* Implement lightweight architectures for efficient performance on mobile devices.
* Real-time processing for quick identification of disease by the application.
* Perform the integration of the deep learning model with a mobile app for seamless disease detection.

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