Major Project-II Report on

An AI-Powered Advisor App for Modern Agriculture Problems

Submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

by

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DECLARATION

We hereby *declare* that the Major Project-II Work Report entitled ***"An AI-Powered Advisor App for Modern Agriculture Problems"*** , which is being submitted to the **National Institute of Technology Karnataka, Surathkal**, for the award of the Degree of Bachelor of Technology in Information Technology, is a *bonafide report of the work carried out by us.* The material contained in this Major Project-II Report has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

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as the record of the work carried out by him/her/them, is *accepted as the B.Tech. Major Project-II work report submission* in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Information Technology in the Department of Information Technology, NITK Surathkal.

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ABSTRACT

This paper provides the details about an application which would help the farmers in multiple ways. It provides with a comprehensive interface where the farmers can predict the most suitable type of crop to be grown in the given conditions, predict the disease from images of the crops, make them aware about the various schemes and grants that the government has made for them, help them improve the understanding about the use of pesticides and all of this could be done in their native language with the help of their voice. Thus it would not be restricted only to the people who know a certain language but everyone who is into farming can seamlessly use this application to get their farming related queries answered. It is thus a real time application development, which we plan to deploy once its completion, which the farmers can make use of.

Keywords— Interface, Grants, Disease, Pesticides, Native language

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CHAPTER 1

INTRODUCTION

1.1 Overview

Smart agriculture has become an essential field of research, seeking to integrate advanced technology into farming practices to boost productivity, ensure sustainability, and empower farmers. This project presents a comprehensive smart agriculture platform designed to address the multi-faceted challenges faced by farmers, particularly those in developing countries such as India. The platform is composed of six main modules: Most Suitable Crop Prediction, Pesticide Recommendation, Crop Disease Prediction, Scientific Approach for Crop Selection, Scheme and Subsidy Awareness, and a Multilingual System for user interaction.

The Most Suitable Crop Prediction Module leverages data on temperature, humidity, soil pH, rainfall, and other environmental factors to recommend crops that are most likely to thrive in a specific region. Machine learning and deep learning techniques, such as Decision Trees, Random Forests, SVMs, and Neural Networks, are utilized to create reliable and region-specific models. The model's accuracy is optimized through cross-validation and hyperparameter tuning, ensuring that farmers receive dependable guidance on crop selection.

The Pesticide Recommendation Module supports sustainable pest management by offering tailored pesticide recommendations. It has three components: crop-specific pesticide suggestions, disease-targeted pesticide recommendations, and a tool to identify suitable crops for a provided pesticide product based on label extraction. This ensures informed usage of both organic and inorganic pesticides, fostering better crop health and reduced environmental impact.

The Crop Disease Prediction Module enables farmers to quickly diagnose crop diseases by analyzing images uploaded to the platform. Using CNN-based models, such as ResNet, paired with pre-processing techniques like resizing, noise removal, and normalization, this module provides reliable disease classification. Farmers can act swiftly with appropriate interventions, preserving crop health and yield.

The Scientific Approach for Crop Selection Module addresses the issue of unscientific crop selection by integrating demand forecasting into decision-making. By collecting historical crop production data, market prices, and demand trends, alongside local factors like soil quality and climate, this module recommends crops that align with market demands and regional conditions. Techniques such as time series forecasting, regression analysis, and ensemble models are applied to predict future demand, helping farmers choose crops that maximize profits while maintaining soil health and crop rotation practices.

The Scheme and Subsidy Awareness Module simplifies access to government support by collecting and organizing data on agricultural schemes and subsidies. This module employs web scraping and data embedding techniques to provide personalized information to farmers, ensuring they are aware of and can access financial assistance.

The Multilingual System Module enhances user accessibility by allowing farmers to interact with the platform in their native languages. This involves the integration of Automatic Speech Recognition (ASR), Natural Language Processing (NLP), and Text-to-Speech (TTS) technologies. The module collects and preprocesses language data, fine-tuning models to understand and respond to spoken input, enabling seamless real-time voice interactions. The multilingual capability ensures that even farmers with limited literacy can access the platform's features, promoting inclusivity.

1.2 Motivation

The motivation for this project arises from the pressing need to bridge the gap between advanced technological solutions and the practical needs of farmers, particularly in regions where agriculture is a cornerstone of economic and social stability. Indian agriculture is characterized by its diversity in crops, climates, and farming practices, yet many farmers lack the knowledge and tools necessary for optimal decision-making. This can lead to challenges such as poor crop selection, ineffective pest management, preventable crop diseases, and underutilization of available government schemes.

The Most Suitable Crop Prediction Module is motivated by the need to assist farmers in choosing the best crops for their specific conditions, reducing risk, and increasing yields. By basing recommendations on empirical data and advanced algorithms, this module empowers farmers to make informed decisions that promote sustainable farming practices.

The Pesticide Recommendation Module aims to ensure that farmers have access to accurate information about pesticide usage. Inappropriate or excessive pesticide use can harm the environment, reduce crop yield, and pose health risks. This module promotes informed and balanced pesticide use, supporting both productivity and ecological health.

The Crop Disease Prediction Module was developed to address the challenges associated with timely and accurate diagnosis of crop diseases. Early and precise identification allows farmers to take preventive or corrective measures, safeguarding their crops and preventing significant financial loss.

The Scientific Approach for Crop Selection Module responds to the issue of market-driven decision-making. By incorporating demand forecasting and market analysis, farmers are equipped with the insights needed to choose crops that align with market trends, stabilizing prices and boosting income. This module also promotes crop rotation and sustainable practices to ensure long-term soil health and reduced pest risks.

The Scheme and Subsidy Awareness Module is inspired by the underutilization of government support programs. By creating a user-friendly, centralized source of information, farmers are better positioned to take advantage of financial assistance, which can be vital for improving their livelihood and productivity.

The Multilingual System Module underscores the importance of accessibility. Language and literacy barriers often prevent farmers from using digital tools. By incorporating voice-based, multilingual capabilities, this project ensures that even farmers in remote and low-literacy areas can access vital information and guidance, thus promoting equitable use of technology.

Together, these modules form an integrated solution designed to empower farmers with the knowledge and resources they need to make informed decisions, improve productivity, and contribute to sustainable agricultural development.

CHAPTER 2

LITERATURE REVIEW

2.1 Background and Related Works

This section explores the current state of research and development in smart agriculture. In order to get the recent issues faced by farmers, we worked on the ground level and spoke to farmers and tried understanding the problems which they face in their day to day life while planting crops. According to them, large companies selling seeds and pesticide kits have thoroughly studied the entire process. These companies provide farmers with schedule cards that instruct them to spray specific pesticides at regular intervals. However, farmers often don't know the chemical composition of these pesticides. This lack of knowledge leads to over-spraying, causing problems throughout the crop's life cycle. This issue is particularly prevalent for crops that aren't in high demand, where there's a scarcity of proper research.

Another major concern they expressed was the selection of the next crop after the three-month potato harvest. Typically, farmers simply follow their peers' choices—an unscientific approach that often leads to oversupply, driving prices down and ultimately reducing their earnings. This situation highlights the need for accurate demand forecasting.

Talking to a few other farmers in the city of Belagavi gave us some interesting insights. Among their concerns for future crop pricing, there was an overall lack of access to useful information related to government research and subsidies. This issue is exacerbated by the fact that most of this research is in English and not translated into vernacular languages.

To obtain domain specific knowledge and to understand what are some of the projects that agricultural institutions are working on, we scoured through various institutions to get an idea.

University of Agricultural Sciences, Dharwad, a major project is contributing to the dissemination of Agromet Advisory Services through publications, outreach initiatives, and digital platforms to support farmers in managing climate-related challenges in agriculture. They are also proactively researching on crop and pest management, focusing on various crops like maize, chickpea, groundnut, cotton, soybean, tomato, onion, okra, sugarcane, and buckwheat. Their work includes studying the efficacy of botanical and chemical formulations against pests and diseases, breeding climate-resilient varieties, optimizing pest control strategies, and developing AI-based tools for timber identification. They also explored agro-waste management, iron chlorosis tolerance in groundnuts, and reviving traditional rice-prawn farming systems to enhance crop productivity and improve farmer income.

University of Agricultural Sciences, Bengaluru, is leading approximately 280 projects focused on enhancing agricultural productivity and sustainability. These projects involve developing high-yield, disease-resistant varieties of key crops like paddy, maize, and pulses. Researchers are addressing major agricultural challenges such as pest infestations, including those caused by the fall armyworm and stem borers, as well as diseases like rust in wheat and blight in tomatoes. The university is also exploring sustainable farming practices, such as organic farming and crop rotation, to reduce chemical inputs and improve soil health. Soil fertility is being enhanced through innovative techniques that balance nutrient levels and improve soil structure. With climate change posing a growing threat, the university is working on developing climate-resilient crop varieties and strategies to help farmers adapt. Additionally, precision agriculture techniques, such as the use of drones and sensors, are being integrated to optimize farming practices.

Research on vegetable crops has been a pivotal area within horticultural sciences, with significant emphasis on improving yield, quality, and resistance to diseases. The Division of Vegetable Crops at the **Indian Institute of Horticultural Research (IIHR), Bengaluru**, has made extensive contributions in this field, focusing on a wide range of crops including tomato, brinjal (eggplant), chili, capsicum, onion, okra, amaranthus, cucurbits, beans, peas, cole crops, and root and tuber crops. One of the primary research areas at IIHR has been breeding and genetic improvement, with numerous studies aimed at developing high-yielding and disease-resistant varieties. For instance, research has led to enhanced tomato varieties with better resistance to pests and improved shelf life, as well as cultivars of chili and capsicum with greater heat tolerance and fruit quality. Additionally, IIHR has been at the forefront of optimizing crop management practices to boost productivity, introducing innovative agronomic techniques such as precision irrigation and integrated nutrient management, which have shown significant improvements in yield and resource-use efficiency. Pest and disease management is another critical area, where integrated pest management (IPM) strategies combining biological control agents with traditional methods have effectively reduced pest incidence while minimizing environmental impact. Post-harvest technology research at IIHR has also played a crucial role in maintaining the quality and extending the shelf life of vegetable crops, with advancements in controlled atmosphere storage and novel packaging materials significantly reducing spoilage. Beyond technical advancements, IIHR has explored the socio-economic impact of vegetable crop research, demonstrating how improved varieties and practices have increased income and improved livelihoods for smallholder farmers. Extension services have been key in disseminating research findings to the farming community. Despite these advancements, gaps remain in the literature, particularly in the areas of long-term sustainability of intensive cropping systems and the development of climate-resilient vegetable varieties. This project aims to address some of these gaps by focusing on specific areas of research that have yet to be fully explored.

Moving over to computer based work on this field, Brahimi et al. [1] proposed a deep learning model for diagnosis of multiple plant diseases by using an AlexNet architecture and reported promising performances. However, they stated that though CNNs achieve an excellent performance under controlled conditions, their precision decreases in the case of field conditions, when considering variable lightings and leaf orientations among others.

However, studies such as that by Satpute et al. [2] emphasize the importance of integrating real-time weather data and advanced sensors to further refine crop prediction models. This integration is crucial for developing dynamic models that can adapt to changing environmental conditions.

Most of the available systems are designed for product recommendations rather than policies. Bhardwaj et al. [3] investigated the adoption of rule-based systems for recommendation of government schemes based on the profile of farmers. It is envisioned that such systems will go a long way in improving awareness and participation by farmers.

Pesticide use management is one of the most important aspects for sustainable agriculture, and it is also one area where the farmers are least guided. Various studies, such as the one by Patel et al. [4], focus on developing recommendation systems with expert opinions on pesticide usage. Most of these have traditional and knowledge-based rules, making them poorly scalable and adaptable.

Most of the time, language becomes one of the major reasons creating barriers to adopting technology in agriculture due to the diverse linguistics in certain regions. Reddy et al. [5], on the other hand, have developed a multilingual chatbot for agriculture that takes questions from farmers in their native languages. Their system enhanced accessibility and had certain limitations due to the accuracy of NLP models handling multiple languages.

With the development of even more robust NLP models, such as BERT and its variants, there is great potential for more accurate and responsive systems that can understand and process queries in a wide range of languages. In this way, all farmers will be able to exploit every technological development, regardless of their proficiency in the use of a language.

2.2 Outcome of Literature Review

Traditional crop prediction models are limited by their reliance on static data. The literature review highlights the potential of machine learning models enhanced by real-time environmental data, to provide more accurate and dynamic crop predictions.

Current literature emphasizes the efficacy of current models in plant disease detection, but there is a notable gap in the application of these models in diverse and real-world agricultural settings. The literature suggests a need for more robust models that can perform well under varying environmental conditions, such as different lighting and leaf orientations.

Results from this literature review clearly indicate gaps in existing research and technological applications in smart agriculture, related to the aspects of plant disease detection, crop prediction, recommendation of government schemes, pesticide management, market-driven crop selection, and multilingual accessibility. ON the ground level, we need all these features in a single application which will help farmers tailored to conditions which are local to them. This tool will be designed to bridge these gaps by integrating an advanced machine learning model with real-time data and user-friendly multilingual interfaces. This will therefore finally equip farmers with better decisions, increase agricultural productivity, and improve the quality of life.

2.3 Problem Statement

Empowering Farmers through Smart Agriculture: Addressing Crop Health, Optimal Pesticide Usage, and government scheme awareness using AI-Driven multilingual solutions.

The project addresses the farmer's critical challenges related to the exact detection of a plant's disease, proper choice of crop and pesticides, and Government schemes and alerts. The solution aims at empowering farmers with AI-driven decisions related to personalized recommendations about crop management, pesticide usage, and availability of government support. Moreover, it will be available in regional language as well.

2.4 Objectives of the Project

(1) Based on the conditions provided by farmers, the system can predict the most suitable crops to grow.

(2) Improve farmer's understanding of pesticide composition and usage to prevent over-spraying and associated crop life cycle issues

(3) Analyze photos of leaves and plants taken by farmers and suggest the possible disease affecting the crop.

(4) Suggest schemes and grants given by the Indian government which will be useful for farmers.

(5) Develop a data-driven, scientific approach for crop selection to avoid oversupply and price drops.

(6) Make an application which takes inputs from the farmers in their native language and processes their query and gives them answers accordingly in their

native language, both in voice and written format.

CHAPTER 3

PROPOSED METHODOLOGY

The proposed work, as covered before will comprise of six objectives or modules. The workflow diagram of the project is displayed in fig. 3.1. A deep dive of the modules is given in the subsequent subsections.

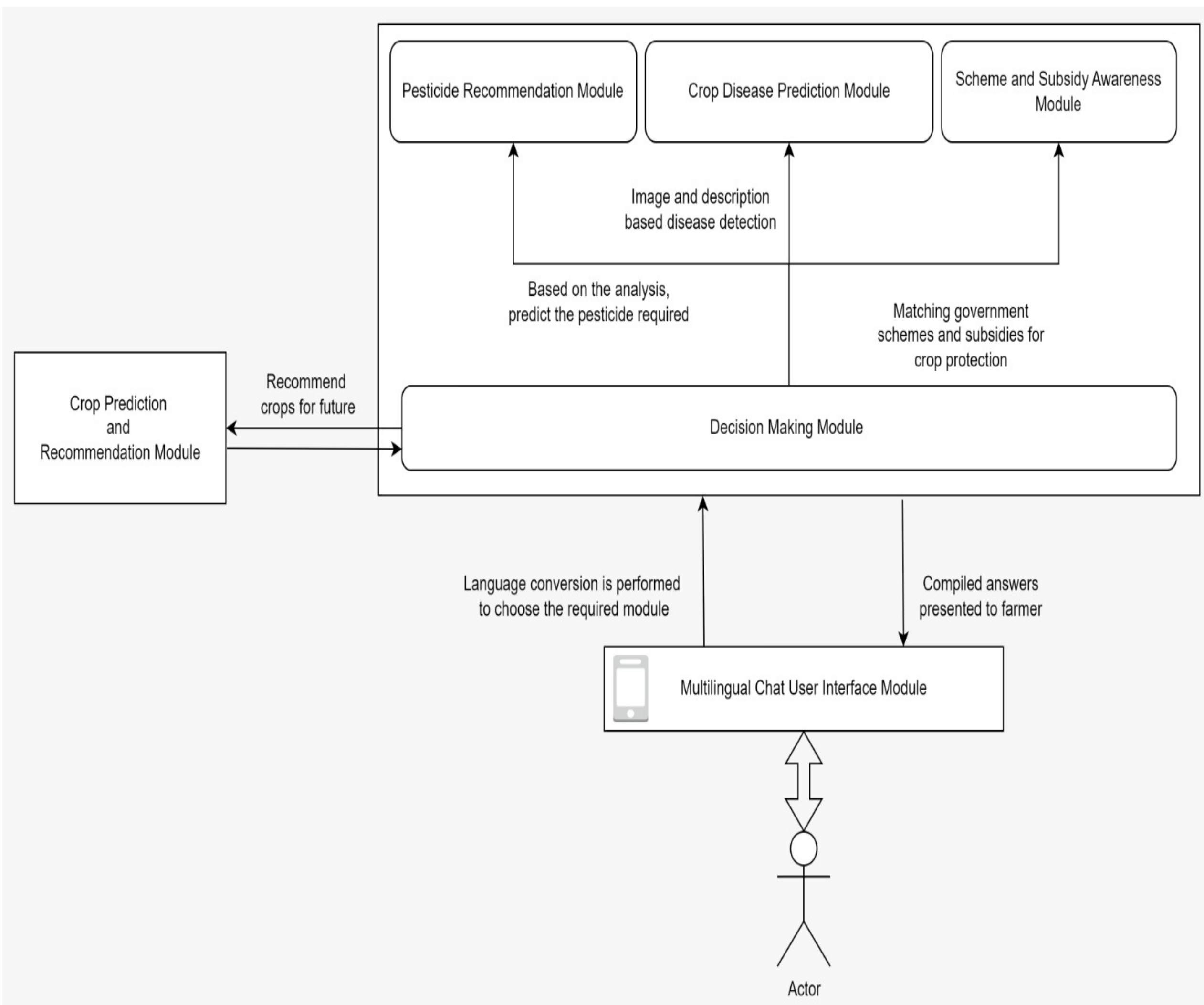

Figure 3.1: Flow Diagram of the proposed work

3.1 Most Suitable Crop Prediction Module

In order to predict the most suitable crop that could grow, firstly we need to collect data with features like temperature, humidity, pH of the soil, rainfall and other relevant parameters which we will get by talking to domain-specific experts in due time. Use of techniques like Principal Component Analysis (PCA) if needed to reduce the number of features while retaining essential information. Then, a plethora of different machine learning/ deep learning algorithms that best suits the data, such as Decision Trees, Random Forests, or even advanced algorithms like Support Vector Machines and Neural Networks. For model performance assessment, we plan to use cross-validation to avoid overfitting. Extensive hyperparameter tuning using Grid Search or Random Search will also be performed. We plan to keep this domain specific to regions nearby and by talking as much as possible to domain experts. This model does not consider the economics and just tells what are the suitable crops based on the environmental information.

3.2 Crop - Pesticide Recommendation Module

This module is divided into three parts the first of them takes the crop name and provides with the name of all the organic pesticides that the farmer could be using for that particular crop, for achieving it we have made a rich dataset which stores all the pesticides for the crops grown.

The second part takes in the name of the disease as predicted by the disease prediction module and gives the name of all the organic as well as the inorganic pesticides that could be used to cure that disease for that particular crop.

The third part would be used when a farmer already has a pesticide packet and wants to know on which crop it should be used and how to use it. For recommending the best suited crops for the given pesticide content image, we plan to extract the content of the image that the farmer has supplied and get the necessary information out of it. After the extraction of the information we convert them into embeddings. On the other hand we have crop database which has the necessary nutrients it needs for its growth. As you can observe in 3.2.1 the flow diagram of the recommendation system is made. We perform a similarity search on the crop requirements and the content of the pesticide image which the farmer has given, if the similarity passes a minimum threshold then that pesticide can be recommended for those particular crops.

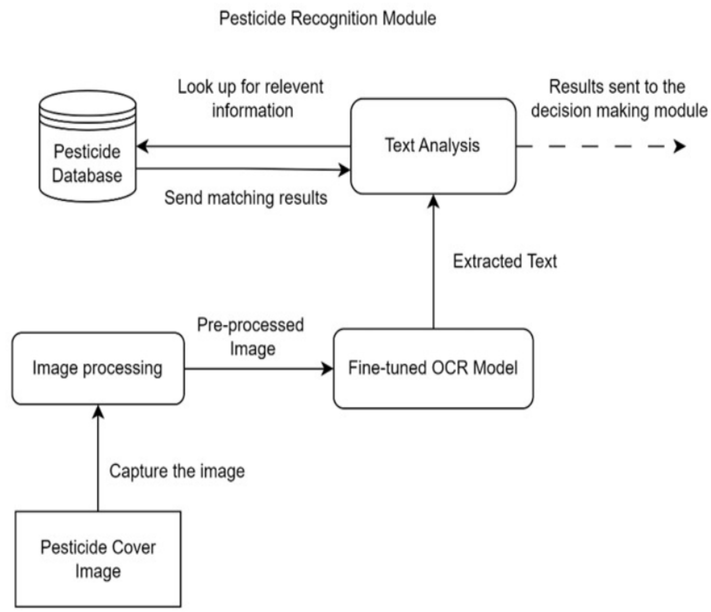

Figure 3.2: Flow Diagram of pesticide recommendation model

3.3 Crop Disease Prediction Module

The image of healthy and diseased crops of high quality will be collected preferably from experts here. Image quality is standardized by resizing, removal of noise, normalization, and enhancement of contrast as you can observe in **??**. Various different features can be extracted using the CNN. We can start with basic machine learning models learning like SVM, Random Forests, and then diving into advanced deep learning like CNNs, VGG16, and ResNet for classification. The dataset is divided into training and testing subsets-the model shall be trained on the training data, and performance shall be evaluated on test data -accuracy. The accuracy of results shall also be compared with the existing methods of literature. Finally, a user-friendly application should be made wherein farmers can upload images of their crop for disease detection and diagnosis.

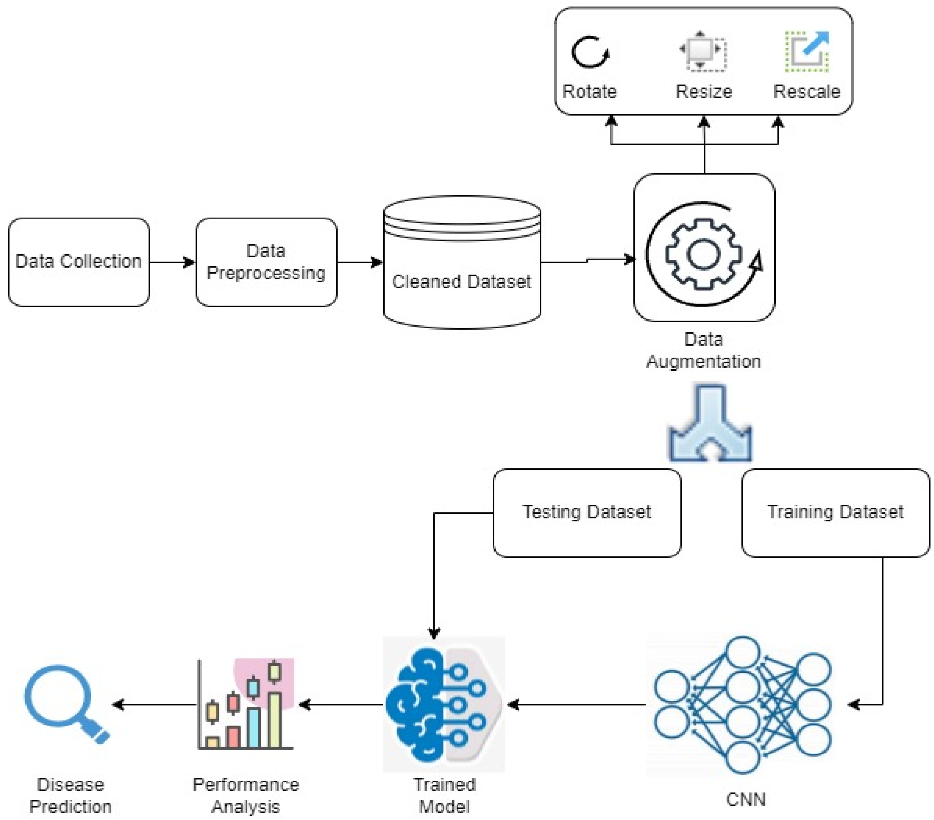

Figure 3.3: Flow Diagram of Disease Prediction model

3.4 Scheme and Subsidy Awareness Module

Collection of data related to Indian Government schemes and subsidies related to agriculture from official government portals will first be performed and converted to embeddings. We plan to implement web scrapers to do the same. This includes schemes under PMFBY (Pradhan Mantri Fasal Bima Yojana), PM-KISAN, crop insurance schemes, state-specific subsidies, etc. Then, organization of the data based on features such as state-specific schemes, crop-specific schemes, eligibility criteria and benefits. Ensuring that the data is up to date and contains the latest policies is a must.

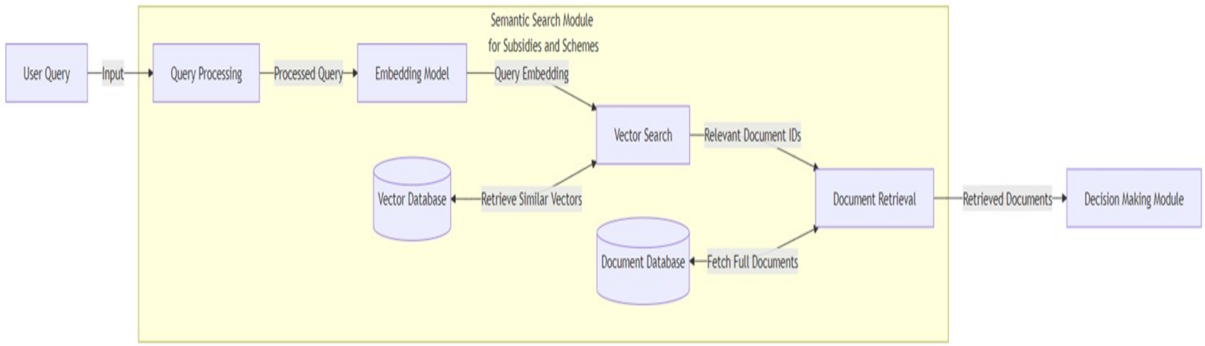

Figure 3.4: Flow Diagram of Scheme Recommendations model

3.5 Scientific Approach for Crop Selection

To address the issue of unscientific crop selection we propose a data-driven approach that integrates demand forecasting to guide farmers in making informed decisions. The methodology begins with the collection of historical crop production data, market prices, and demand trends from various sources such as government agricultural departments, market reports. Additionally, local factors like soil quality, climate conditions, and previous crop yields will be taken into account to tailor recommendations to specific regions.

Using this data, machine learning models will be developed to forecast future demand for various crops. These models will analyze past patterns of oversupply and undersupply, predicting which crops are likely to yield better market prices based on current trends. Techniques such as time series forecasting, regression analysis, and ensemble models will be employed to ensure accuracy. The system will also factor in crop rotation practices and environmental sustainability to maintain soil health and reduce the risk of pests and diseases. This scientific approach aims to minimize the risk of oversupply, stabilize prices, and ultimately increase the farmers' earnings while promoting sustainable agricultural practices.

3.6 Multilingual System Module

Development of a multilingual module, which would allow farmers to state a query in their native language and receive a voice response back in the very same language, requires several steps. These steps include gathering and preprocessing relevant language data, namely collecting speech and text datasets in the target languages with the special focus on agricultural vocabulary. Then, speech datasets have to be transcribed into text; further, speech and text data should be cleaned and normalized. Pre-trained Automatic Speech Recommendation models can be further fine-tuned on this data so that it can identify the spoken input correctly and convert it into text. Recognized text, then, is processed using NLP models that are trained on the classification of a query's intent and the extraction of relevant entities, possibly crop names or symptoms for some sort of disease, or perhaps which crop to grow, etc.

Once the spoken input has been understood, the system forms a response that is converted back into speech using the TTS models. These models are fine-tuned for each target language to produce natural speech with proper prosody and clarity. The integrated system is going to assemble ASR, NLP, and TTS modules into an end-to-end voice interaction pipeline that will allow farmers to communicate in real time with the system by using a user-friendly interface. This interface is designed to support voice input and voice output, which will help farmers with total ease of access to the features of the system, even in places where literacy is low. The system should allow for low latency, can be deployed on cloud platforms, and has an offline functionality option for places that have poor internet connectivity.

CHAPTER 4

WORK DONE, RESULTS AND ANALYSIS

The crop that was decided to work on was Paddy (Rice). Paddy was chosen because of it's popularity in Karnataka and the high amounts in which it is grown. The work associated with each module has been described thoroughly in detail in the following subsections.

4.1 Crop Disease Prediction Module

4.1.1 Introduction

Rice (paddy) is a staple crop cultivated extensively across Karnataka and is vital to the agricultural economy. However, rice production faces critical challenges from various diseases, including both fungal and bacterial infections, which can drastically reduce yield and crop quality.

Common diseases affecting rice include rice blast, sheath blight, and bacterial leaf blight, all of which pose significant risks to crop health. These diseases, intensified by changing climate and environmental conditions, threaten to impact rice productivity on a large scale.

To address these challenges, deep learning has emerged as a promising approach for early disease detection in crops. This module leverages deep learning techniques, namely the Convolutional Neural Network (CNN) to accurately identify and predict major rice diseases, enabling farmers to take timely preventive measures and enhance crop management effectively.

4.1.2 Literature Review

Prevalent Paddy Diseases in Karnataka

Rice cultivation in Karnataka faces significant challenges due to various fungal and bacterial diseases that severely impact crop yield and quality. Surveys conducted across rice-growing districts have identified rice blast, sheath blight, and grain discoloration as primary threats [6]. Leaf blast and sheath blight are particularly prevalent in Mandya and Yadgir, driven by specific microclimatic conditions that favor their spread. Notably, grain discoloration, primarily caused by the fungus Curvularia lunata, affects both yield and quality, making it a crucial concern for farmers in these regions.

In the Cauvery command area, one of Karnataka's key rice-producing zones, bacterial diseases have recently emerged alongside traditional fungal threats like blast and sheath blight. Studies report that bacterial leaf blight (BLB) and bacterial leaf streak have shown a consistent presence in the last five years, increasing the overall disease burden on rice crops and compounding yield losses in this region [7]. Additionally, sheath blight continues to pose a significant risk in the area due to favorable environmental conditions, such as high humidity and water stagnation, which exacerbate disease spread [8].

Recent literature highlights neck blast as a particularly destructive disease, with no currently resistant varieties available to mitigate its impact. Unseasonal rains have intensified this disease, causing heavy yield losses across multiple regions. The spread of minor diseases like udbatta stem rot and false smut into new areas further complicates disease management efforts [9].

The outome of the literature survey highlighted key diseases affecting Karnataka's rice crops include blast, bacterial blight, sheath blight, sheath rot, udbatta, false smut, and root knot disease. Given the availability of relevant datasets, bacterial leaf blight, bacterial leaf streak, bacterial blight, sheath blight, brown spot, and blast were selected as focal diseases for predictive modeling in this study.

ML Based methods for Rice Disease Identification

Various machine learning techniques are utilized for detecting diseases in rice plants. Researchers have developed innovative algorithms to improve the accuracy of disease identification.

Ahad et al. propoposed a model which leverages MobileNet and and data augmentation techniques to detect four types of rice plant diseases using a public dataset. The use of filter visualization and activation maps further demonstrated its interpretability [10].

Ganatra and Patel explored image processing methods for rice disease classification. Their approach involved extracting key features such as color, shape, and texture from leaf images, which were then classified using well-established machine learning models on a public dataset [11].

Bhartiya et al. proposed machine learning-based approach focusing on feature extraction and classification. By utilizing shape features such as area, roundness, and lesion-to-area ratio, the study achieved an accuracy of 81.8% using a Quadratic SVM classifier [12].

Kitpo and Inoue the critical role of feature extraction for image classification tasks in machine learning applications [13]. Building upon this insight, Gayathri Devi and Neelamegam demonstrated how combining an SVM with a feature extraction techniques like discrete wavelet transform, scale invariant feature transform and gray scale co-occurrence matrix gives superior results. Their study confirmed that integrating classical machine learning with smart feature extraction the identification of rice leaf diseases [14].

DL Based methods for Rice Disease Identification

Verma et al. proposed a lightweight CNN model is proposed for disease detection in Corn, Rice, and Wheat, achieving 84.4% accuracy with only 387,340 parameters [15]. It outperformed some standard CNN models.

Upadhyay et al. proposed a model which applies Otsu's global thresholding technique to perform image binarization to remove background noise of the image before applying a CNN to detect diseases [16].

Yakkundimath et al. used transfer learning with VGG-16 and GoogleNet CNN models for rice disease classification, achieving 92.24% and 91.28% accuracy, respectively. It demonstrates practical application for on-field disease diagnosis using 12,000 labeled images [17].

As a result of the literature review, we saw that there is no existing dataset focusing on the diseases prevalent in Karnataka. So, the first major contribution is curating a dataset specific to Karnataka and the second contribution is to use data augmentation techniques to enhance robustness of the CNN model and enhanced accuracy.

4.1.3 Dataset Collection

The first step of the module was to gather relevant datasets, ensuring a wide range of images capturing different diseases affecting rice crops. Three datasets were chosen for this purpose. The *Rice Disease Dataset* includes images of bacterial leaf blight, brown spot, healthy rice leaves, leaf blast, leaf scald, and sheath blight, providing a broad representation of key diseases and healthy samples. The *Paddy Doctor: Paddy Disease Classification* dataset contains images of normal rice crops as well as diseases such as tungro, hispa, downy mildew, dead heart, brown spot, blast, bacterial panicle blight, bacterial leaf blight, and bacterial leaf streak. Lastly, the *Rice Leaf Disease Image Samples* dataset focuses on images of bacterial blight, blast, brown spot, and tungro. Together, these datasets offer comprehensive coverage of common rice diseases, supporting accurate model training for disease prediction.

Out of these, the images for Sheath Blight, Normal, Brown Spot, Blast, Bacterial Leaf Streak, Bacterial Leaf Blight and Bacterial Blight were used for training and inferencing our models as they were more prevalent in Karnataka.

Figures 4.1 and 4.2 show the diversity in the chosen dataset. Both images are of the disease, Bacterial Leaf Blight but figure 4.1 shows a far view of the disease and figure 4.2 shows a closer view of the disease. A farmer can thus take pictures in different manners to get results from our models.

4.1.4 Data Augmentation

To correct the imbalance in the dataset and also increase the robustness of the modelling, data augmentation was done. The following data augmentation techniques were applied to enhance the dataset:

- **Random Affine Transformation**: This technique applied random rotations (up to 40 degrees), translations (shifting the image up to 20% in both x and y directions), and scaling (adjusting the image size by a factor between 0.8 and 1.2) to create variations of the original images.

Figure 4.1: Far view picture of Bacterial Leaf Blight

Figure 4.2: Near view picture of Bacterial Leaf Blight

- **Random Horizontal Flip**: Images were randomly flipped horizontally, which helps the model learn features that are invariant to horizontal orientation.

- **Random Crop**: After resizing, a random crop of 224x224 pixels was taken from the resized images, which helps the model focus on different parts of the images and learn from various perspectives.

These techniques collectively aimed to enhance the robustness of the model and address class imbalance, ensuring effective prediction and classification of various rice diseases, even when images were altered or presented in different conditions. Figures 4.3 and 4.4 show the label distributions before and after data augmentation, respectively.

The final dataset consisted of 9249 training images and 2308 test images.

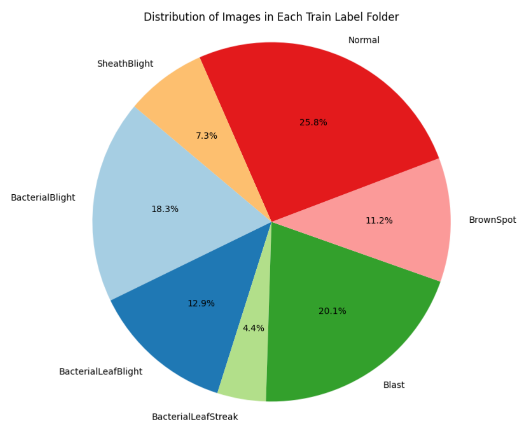

Figure 4.3: Label distribution before data augmentation

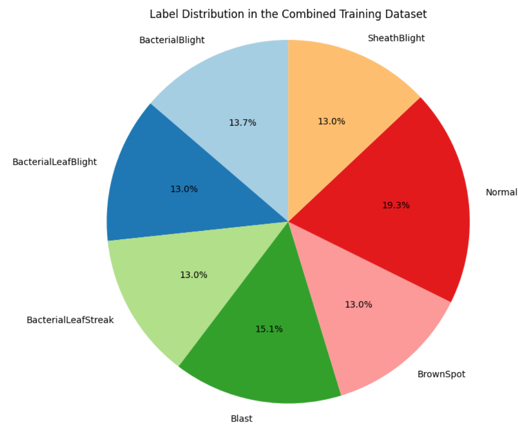

Figure 4.4: Label distribution after data augmentation

4.1.5 Method 1: Adaptive Learning Rate and Mixed Precision Training for Efficient Convergence

This study implements a robust training framework for the identification of plant diseases using state-of-the-art ResNet models. It enhances convergence efficiency by leveraging dynamic learning rate scheduling and mixed precision techniques.

Model Initialization

Pre-trained convolutional neural network (CNN) models, such as ResNet-50 [18], were selected for transfer learning. The fully connected (fc) layer of each model was modified to match the number of output classes, enabling effective feature extraction while reducing computational complexity.

Data Preparation

The dataset was divided into training and validation subsets. Data loaders were employed to feed batches of 32 images into the models during training. The training data was shuffled to improve model generalization [19].

Training Process

The training process was conducted for 10 epochs using the Stochastic Gradient Descent (SGD) optimizer with a momentum value of 0.9. The key innovations in the training process were:

- **Mixed Precision Training:** To accelerate training and reduce memory consumption, mixed precision training [20] was employed using the Automatic Mixed Precision (AMP) module in PyTorch. This method dynamically selects between 16-bit and 32-bit floating-point arithmetic, preserving numerical stability while improving training speed.

- **Warm-Up Phase with LambdaLR:** For the initial two epochs, a warm-up scheduler was employed, gradually increasing the learning rate from 0 to the base learning rate (0.001). This approach prevented instability during early training by allowing the model to adapt to the initial weights incrementally [21]. The LambdaLR scheduler defined the learning rate as:

$$\eta(t) = \frac{t}{T_w} \cdot \eta_0, \quad \text{for } t \leq T_w$$

  where t is the current epoch, T_w is the number of warm-up epochs, and η_0 is the base learning rate.

- **Cosine Annealing Phase:** After the warm-up phase, the learning rate was adjusted using a cosine annealing scheduler [22], which decayed the learning rate according to a cosine function:

$$\eta(t) = \eta_{\min} + \frac{1}{2}(\eta_0 - \eta_{\min}) \left(1 + \cos\left(\frac{\pi t}{T_c}\right)\right)$$

  where T_c is the total number of training epochs, and $\eta_{\min}$ is the minimum learning rate. This technique allowed smoother convergence and prevented premature stagnation in model performance.

Loss Function

The cross-entropy loss function was utilized to compute classification errors, providing robust feedback for backpropagation.

Evaluation

The model performance was evaluated based on validation accuracy, training loss, and validation loss. The best model weights were saved whenever an improvement in validation accuracy was observed.

This training methodology, leveraging warm-up and cosine annealing strategies, ensured efficient learning and convergence while maintaining high generalization capability.

4.1.6 Method 2: Hybrid Feature Extraction

This method integrates convolutional neural network (CNN) features with handcrafted feature extraction techniques to enhance plant disease classification. Unlike a purely deep learning-based approach, this method improves feature representation by combining learned and handcrafted features before classification using a neural network.

Model Initialization

This method employs multiple state-of-the-art CNN architectures, including ResNet-50, SE-ResNet-50, ResNeXt-50, and ResNeSt-50. Each of these models is pre-trained on ImageNet and serves as a feature extractor by removing the fully connected layer, retaining only convolutional feature representations.

- **ResNet-50**: The ResNet-50 model [18] employs residual learning with skip connections, allowing gradients to flow more efficiently during training. This mitigates vanishing gradient issues and enables deeper networks to be trained effectively.

- **SE-ResNet-50**: This model extends ResNet-50 by incorporating Squeeze-and-Excitation (SE) blocks [23], which adaptively recalibrate channel-wise feature responses to emphasize informative features.

- **ResNeXt-50**: Introduced by Xie et al. [24], ResNeXt-50 improves feature learning by using grouped convolutions, which enhance the model's representational capacity without increasing computational complexity.
- **ResNeSt-50**: This model builds on ResNeXt by introducing Split-Attention [25], where multiple feature representations are adaptively combined using attention mechanisms, leading to improved performance.

Handcrafted Feature Extraction

In addition to deep CNN features, this method incorporates handcrafted features such as color, texture, and shape descriptors to enrich feature representation. The following handcrafted features are utilized:

- **Histogram of Oriented Gradients (HOG)**: HOG captures local shape and edge orientations by computing gradient histograms in small spatial regions [26]. This feature is useful for distinguishing structural patterns in diseased leaves.
- **Gray-Level Co-Occurrence Matrix (GLCM)**: GLCM extracts texture features based on spatial relationships between pixel intensities [27]. Features such as contrast, correlation, energy, and homogeneity are derived from the GLCM matrix to analyze texture variations in diseased regions.
- **Local Binary Patterns (LBP)**: LBP is a texture descriptor that encodes pixel intensity differences between a central pixel and its neighbors [28]. It is particularly effective for identifying surface patterns in plant diseases.
- **Color Histogram**: This feature captures color distribution across images by computing histograms in different color spaces (RGB, HSV) [29]. Since plant disease symptoms often manifest as color changes, this feature aids in disease identification.
- **Shape Descriptors**: Shape-based features such as Hu moments [30] and Fourier descriptors [31] are extracted to characterize the geometric structure of diseased regions.

Feature Fusion

Once deep and handcrafted features are extracted, they are concatenated to form a comprehensive feature vector. This fusion enhances the discriminative power of the representation, ensuring improved classification performance.

Classification

The final feature vector is passed through different classification models to assess their effectiveness in plant disease identification. The classifiers used include a fully connected neural network, as well as traditional machine learning models such as Random Forest, Support Vector Machine (SVM), and Logistic Regression.

- **Neural Network Classifier**: A fully connected neural network was trained using cross-entropy loss and optimized with the Adam optimizer for 30 epochs. The architecture consists of three dense layers with ReLU activation, followed by a softmax layer for classification.

- **Random Forest**: A 100-tree Random Forest classifier was employed to leverage ensemble learning for robust decision-making.

- **Support Vector Machine (SVM)**: An SVM with an RBF kernel was used to map features into higher-dimensional space, enhancing classification performance.

- **Logistic Regression**: A logistic regression model was trained with an increased iteration limit (1000) to ensure convergence and provide a strong baseline performance.

The results and analysis of the three modules are detailed in the subsections below:

4.1.7 Results and Analysis

Method 1: Adaptive Learning Rate and Mixed Precision Training for Efficient Convergence

Following the training, the accuracies of each model are displayed in Table 4.1.

On observing the curves for loss, a steady decrease was observed for both training and validation loss. The validation accuracy also saw a steady increase throughout the training process. There was no overfitting, as both the training and validation accuracies matched throughout.

When compared to results from literature, the ResNet-50 model demonstrated superior performance, achieving excellent results while utilizing minimal computational power. Due to the methods used for faster training and effective convergence, we utilised lesser resources and training time compared to the existing methods in the literature.

Table 4.1: Classification Accuracy of models

Model	**Accuracy (%)**
SE-ResNet-50	88.39
ResNeXt-50	93.41
ResNet-50	**98.96**

Method 2: Hybrid Feature Extraction

The results of our endeavors are summarized in Table 4.2. It is evident that different combinations of feature extractors and classifiers yield varying performances. Among all configurations, the best-performing model was **ResNeSt-50 with Logistic Regression**, achieving an accuracy of **92.50%**.

In general, logistic regression consistently outperformed other classifiers across different feature extractors, reinforcing its reliability for this task. While deep neural networks offered competitive performance, they did not always surpass traditional classifiers, suggesting that simpler models may sometimes be preferable when working with extracted deep features.

We also compared the performance of our models with existing datasets to draw a comparison between existing solutions and our proposed solution to the problem. The datasets selected for this study are publicly available and have been collected and published by government agencies, universities, and research institutes. Specifically, we used the Kaggle Rice Disease Image Dataset [32], the UCI Machine Learning Repository [33], and the Mendeley Rice Leaf Disease Image Samples [34]. These

Table 4.2: Classification Accuracy of Different Models and Classifiers

Model	**Classifier**	**Accuracy (%)**
ResNet-50	Neural Network	88.69
ResNet-50	Random Forest	89.43
ResNet-50	SVM	88.78
ResNet-50	Logistic Regression	91.16
ResNeSt-50	Neural Network	90.90
ResNeSt-50	Random Forest	88.99
ResNeSt-50	SVM	89.04
ResNeSt-50	Logistic Regression	**92.50**
ResNeXt-50	Neural Network	74.48
ResNeXt-50	Random Forest	89.12
ResNeXt-50	SVM	88.91
ResNeXt-50	Logistic Regression	89.90
SE-ResNet-50	Neural Network	87.65
SE-ResNet-50	Random Forest	88.21
SE-ResNet-50	SVM	86.48
SE-ResNet-50	Logistic Regression	88.21

datasets serve as benchmarks, allowing us to evaluate the effectiveness of our hybrid feature extraction approach against prior methods

Table 4.3 presents the classification accuracy of various models across three datasets: Kaggle, UCI, and Mendeley. The models tested include four CNN-based feature extractors: ResNet-50, ResNeSt-50, ResNeXt-50, and SE-ResNet-50. Classification was performed using four different classifiers: Neural Network, Random Forest, SVM, and Logistic Regression.

Overall, the Mendeley dataset exhibited the highest classification accuracy, with most models achieving nearly perfect scores. The UCI dataset also showed strong performance, but some variations were observed, particularly with ResNeXt-50 when paired with SVM and Logistic Regression, where accuracy dropped significantly. The Kaggle dataset posed the greatest challenge, with lower accuracy across all models, though ResNeSt-50 combined with Neural Networks or Logistic Regression yielded the best results.

Among the feature extractors, ResNeSt-50 demonstrated the most consistent and superior performance across datasets, particularly achieving the highest accuracy in the Kaggle dataset. ResNet-50 and SE-ResNet-50 also performed well, maintaining stable accuracy across most datasets. However, ResNeXt-50 struggled in certain cases, especially with the UCI dataset.

Regarding classifiers, Neural Networks consistently provided high accuracy across datasets, often outperforming traditional machine learning models. Random Forest proved to be a strong competitor, achieving 100% accuracy in multiple cases, particularly with the UCI dataset. SVM, on the other hand, exhibited inconsistent results, performing well in some cases while struggling significantly in others. Logistic Regression, despite its simplicity, performed remarkably well, particularly on the Mendeley dataset, where it achieved near-perfect accuracy across all CNN feature extractors.

In conclusion, the combination of ResNeSt-50 with Neural Networks or Random Forest emerges as a robust choice for achieving high accuracy across different datasets. While deep CNN feature extraction significantly enhances classification performance, the choice of classifier plays a crucial role, with Neural Networks and Random Forest generally yielding the best results. These findings highlight the effectiveness of deep learning-based feature extraction and emphasize the importance of dataset characteristics in model performance.

Table 4.3: Classification Accuracy on Different Datasets

CNN Model	**Classifier**	**Kaggle**	**UCI**	**Mendeley**
ResNet-50	Neural Network	78.06	87.5	100
ResNet-50	Random Forest	83.23	100	100
ResNet-50	SVM	80	95.83	100
ResNet-50	Logistic Regression	84.52	100	100
ResNeSt-50	Neural Network	88.06	87.5	99.83
ResNeSt-50	Random Forest	82.9	100	100
ResNeSt-50	SVM	83.87	91.67	100
ResNeSt-50	Logistic Regression	88.06	95.83	100
ResNeXt-50	Neural Network	85.81	83.33	100
ResNeXt-50	Random Forest	80.97	87.5	100
ResNeXt-50	SVM	81.94	66.67	99.66
ResNeXt-50	Logistic Regression	80.97	66.67	99.83
SE-ResNet-50	Neural Network	84.19	91.67	99.33
SE-ResNet-50	Random Forest	82.26	91.67	100
SE-ResNet-50	SVM	80.65	70.83	100
SE-ResNet-50	Logistic Regression	82.9	79.17	99.92

4.2 Crop - Pesticide Recommendation Module

4.2.1 Introduction

The timely treatment of crop diseases is crucial for minimizing crop wastage and ensuring optimal production. However, farmers face significant challenges in effectively utilizing available pesticides due to knowledge gaps in their application and usage. This module addresses these challenges through a comprehensive crop-pesticide recommendation system that provides guidance for both organic and inorganic pesticide usage.

The system leverages a diverse dataset that encompasses detailed information about pesticide applications, focusing on proper usage methods and optimal dosage recommendations to prevent overuse while ensuring effective disease treatment. A key innovation of this module is its integration of Optical Character Recognition (OCR) technology to extract valuable information directly from pesticide packaging. By analyzing details such as ingredients, pH values, and potentially harmful substances, the system can make informed recommendations about pesticide suitability for specific crops.

This module serves as a bridge between farmers and the complex world of pesticide application by providing clear, actionable guidance on which pesticides are appropriate for specific crops, their proper usage methods, and optimal quantities. Whether dealing with organic or inorganic pesticides, farmers can access reliable information about application methods and crop compatibility, enabling them to make informed decisions that protect their crops while maintaining productivity.

4.2.2 Literature Review

Based on the various paddy diseases present in Karnataka, we researched about some of the organic as well inorganic solutions that are currently being used to cure them.

Organic pesticides are valued for their minimal environmental impact and safety in agriculture. A primary organic treatment used in Karnataka is neem oil, which is effective against a range of paddy diseases [35]. Studies highlight that correct dosage per acre and timed applications are crucial for optimal results. Additional organic options, such as garlic extract, chili pepper extract, and fish oil soap, are also widely utilized. Resources from government agricultural sites [36] indicate these alternatives offer pest control benefits with reduced toxicity. For instance, garlic extract acts as an antifungal, while chili pepper extract deters pests effectively.

Inorganic pesticides, though more chemically intensive, offer rapid disease management in paddy fields with high infestation levels. Research shows that the chemical composition and pH of these pesticides significantly affect their effectiveness and safety for paddy crops. Analyzing these factors allows for recommendations on suitable usage, including compatible crop types and best practices to mitigate environmental impact.

4.2.3 Dataset Collection

The dataset for this module was created from reliable sources focused on paddy disease management in Karnataka. Data was collected from agricultural extension publications, government websites, and pesticide regulatory bodies, providing both organic and inorganic pesticide recommendations tailored to common paddy diseases.

To ensure accuracy and relevance, official sources like the Indian Council of Agricultural Research (ICAR), the Central Insecticides Board and Registration Committee (CIBRC), and the Karnataka State Department of Agriculture were referenced. Manufacturer guidelines were also reviewed for specific storage and handling instructions. This dataset thus serves as a comprehensive guide for sustainable paddy disease management practices in Karnataka.

4.2.4 Optical Character Recognition

The crops which are suitable based on the content of the pesticide are recommended using this model. We developed a methodology involving image analysis, embedding conversion, and similarity-based recommendation.

- **Content Extraction in Images:** In the initial stage, images of pesticide labels provided by farmers as you can observe in the figure 4.5 are analyzed to identify chemical components and nutrient composition. Using image processing techniques, we extract relevant textual and graphical information from the image as you can notice in the figure 4.6 ensuring accurate identification of pesticide contents.

- **Embedding Conversion:** Once content is extracted, the information is converted into embeddings. This step involves transforming the extracted data into a structured and quantitative format, allowing for easy comparison and analysis against crop nutrient needs.

- **Crop Database of Nutrient Requirements:** We maintain a comprehensive database of crops with detailed nutrient requirements. This database acts as a reference, holding critical information about each crop's nutrient needs and allowing us to assess compatibility based on pesticide contents.

- **Similarity Search and Recommendation:** In the final stage, the pesticide embeddings are compared with the crop nutrient requirements stored in the database. Using similarity search techniques, we compute a similarity score between the pesticide content and each crop's requirements. If this score meets or exceeds a predefined threshold, we recommend the pesticide as suitable for those crops.

4.2.5 Organic and Inorganic Pesticide Recommendation Based on the Disease Predicted

After predicting the plant disease, this module acts as a guidance system to help farmers select and apply the correct pesticide. It accesses a structured database with detailed information on various pesticides, with columns like Disease, Pesticide Name, and Active Ingredient to identify the best-suited pesticide for the diagnosed disease. The Recommended Quantity column specifies the exact amount to apply per unit area, while Application Interval (days) suggests the ideal frequency of application to maintain effective disease control.

The Method of Application and Target Stage of Crop fields provide further guidance, indicating the recommended application method (e.g., foliar spray, soil drench) and the optimal crop stage for applying the treatment. To ensure safety, the Toxicity Level and Environmental Impact columns inform farmers about potential risks, while

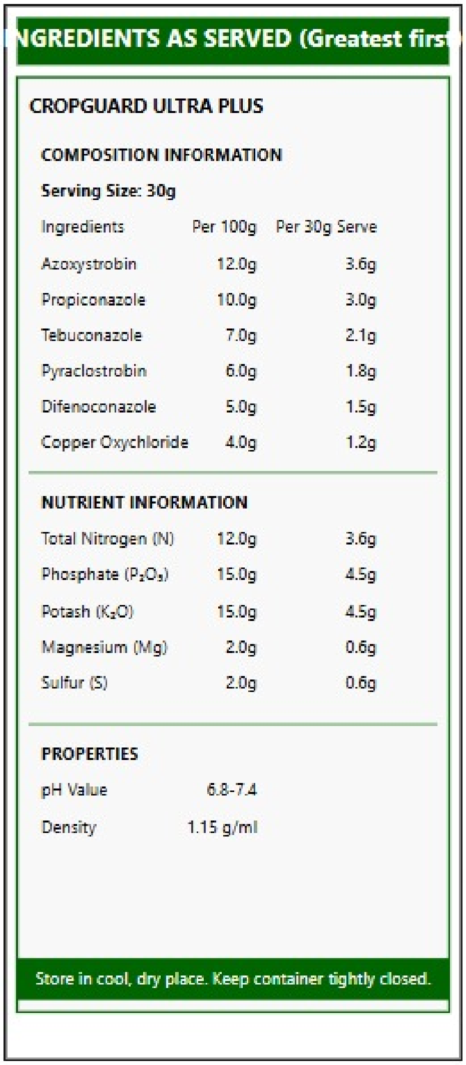

Figure 4.5: Pesticide Packet Content

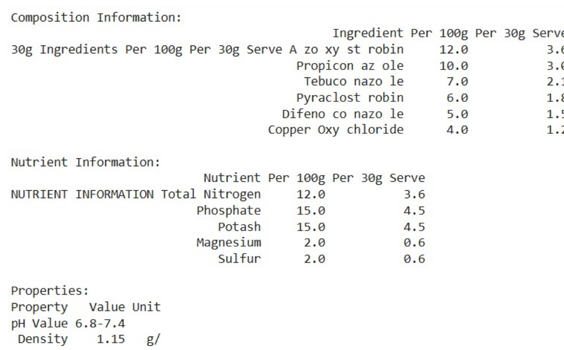

Figure 4.6: The content of the packet after OCR

the Pre-Harvest Interval (PHI) details the minimum required time between the last application and harvest to ensure consumer safety.

The module also includes Cost per Application to assist with budgeting, and Storage Instructions along with Additional Notes to provide practical advice on handling and storing the pesticide. By presenting this structured, actionable information, the module helps farmers apply pesticides safely and effectively, reducing waste and promoting sustainable practices while minimizing environmental risks.

4.2.6 Results and Analysis

After testing out our model on some of the pesticides it was able to predict whether the given pesticide is suitable for paddy or not. By analyzing the content and the active ingredients present it was able to predict the effectiveness of the pesticide by calculating a compatibility score. Also it gave the quantity of the pesticide to be used in various stages of the growth such as seedling, vegetative and reproductive phases.

```
Compatibility Score:
    1.0
Warnings:
    None
Recommendations:
    base_rate:
        2.00 L/ha
    frequency:
        Every 14 days
    timing:
        Early morning or late evening
    weather_conditions:
        - Avoid application before rain
        - Optimal temperature: 20-30°C
        - Wind speed < 10 km/h
    stage_specific:
        seedling:
            1.00 L/ha
        vegetative:
            2.00 L/ha
        reproductive:
            1.50 L/ha
```

Figure 4.7: Shows the compatibility score and the usage directions

Also some of the organic pesticides that can be used are stored in a dataset, thus whenever a user queries for a crop such as rice as in figure 4.8 or any other crop he will be displayed the organic pesticides along with how to use them.

Pesticide Name	Usage Quantity (per acre)	Application Interval (days)	Target Pests	Application Method
Neem Oil	2-3 liters	7-10	Leafhoppers, Stem borers	Foliar spray
BT (Bacillus thuringiensis)	1-1.5 kg	14	Caterpillars	Spray on leaves
Trichoderma	1 kg	15	Root rot, Fusarium wilt	Soil drench/spray
Garlic Extract	500 ml	10	Aphids, Thrips	Foliar spray
Beauveria bassiana	500 g	15	Planthoppers	Foliar spray

Figure 4.8: Shows all the organic pesticides when queried for rice

After the crop disease has been identified using the crop disease prediction module, this module can recommend suitable pesticides tailored to the specific disease detected.

Disease	Pesticide Name	Active Ingredient	Recommended Quantity	Application Interval (days)	Method of Application	Target Stage of Crop	Toxicity Level	Environmental Impact	Pre-Harvest Interval (PHI)	Cost per Application	Storage Instructions	Additional Notes
Bacterial Leaf Blight	Streptomycin sulfate	Streptomycin	120g per acre	15	Foliar spray	Vegetative to booting	Moderate	Low	21 days	₹830 per acre	Store in a cool, dry place, away from sunlight	Avoid application during rainy days
Bacterial Leaf Streak	Copper hydroxide	Copper-based	500g per acre	12	Foliar spray	Early tillering	Low	Moderate	30 days	₹1,245 per acre	Keep tightly closed in original container	Spray in the early morning to maximize effect
Bacterial Blight	Oxytetracycline	Oxytetracycline	100g per acre	10	Foliar spray	Tillering to flowering	High	High	25 days	₹996 per acre	Keep away from food and animal feed	Apply at first sign of symptoms
Sheath Blight	Validamycin	Validamycin	2g per liter of water	7	Spray at the base of plant	Vegetative to panicle	Low	Low	14 days	₹664 per liter	Store in original packaging, away from moisture	Avoid during flowering to prevent stress
Brown Spot	Mancozeb	Mancozeb	300g per acre	14	Foliar spray	Tillering	Moderate	Moderate	14 days	₹747 per acre	Keep in a dry area, protected from heat	Ensure thorough coverage
Blast	Tricyclazole	Tricyclazole	1g per liter	7	Foliar spray	Panicle initiation	Moderate	Low	21 days	₹830 per liter	Store in a well-ventilated area	Avoid overhead irrigation post-application

Figure 4.9: Pesticide suggestions for the disease predicted

4.3 Scheme and Subsidy Awareness Module

4.3.1 Introduction

Indian farmers are often unaware of the various schemes and subsidies available to them. This module aims to bridge this information gap by providing a comprehensive guide to government schemes and subsidies for farmers in Karnataka. By leveraging data from official sources, we offer detailed insights into eligibility criteria, application procedures, and benefits of each scheme, empowering farmers to make informed decisions and access the support they need.

4.3.2 Literature Review

Based on the literature review, we identified several key schemes and subsidies that are relevant to farmers in Karnataka. These include the Pradhan Mantri Fasal Bima Yojana (PMFBY), the Soil Health Card Scheme, and the Rashtriya Krishi Vikas Yojana (RKVY). Each of these schemes offers unique benefits and support to farmers, ranging from crop insurance to soil health monitoring and financial assistance for agricultural projects.

4.3.3 Dataset Collection

To build this module, we collected data from various official sources, including the Ministry of Agriculture and Farmers Welfare, the Department of Agriculture, Cooperation, and Farmers Welfare, and the Karnataka State Government. By aggregating information from these sources, we created a comprehensive database of schemes and subsidies available to farmers in Karnataka, complete with details on eligibility criteria, application procedures, and benefits.

4.3.4 Data Preprocessing

The collected data was in inconsistent formats and required extensive preprocessing to ensure accuracy and consistency. We cleaned the data by removing duplicates, standardizing column names, and filling missing values where possible. We also performed data validation checks to identify and correct errors, ensuring that the information presented to farmers is reliable and up-to-date.

- Data Cleaning: Remove duplicates, standardize column names, fill missing values

- Data Validation: Identify and correct errors, ensure reliability and accuracy

4.3.5 Vectorization and Embedding

Vectorisation is a process of converting text data into numerical data. This is done to make the data compatible with machine learning algorithms. In this module, we used the TF-IDF vectorization technique to convert the scheme descriptions into numerical data. This allows us to perform similarity analysis and recommend relevant schemes to farmers based on their preferences and requirements.

The data is first passed through a tokenizer which breaks down the text into individual words. These words are then converted into vectors using BERt embeddings. These vectors are then passed through a neural network to generate a final vector representation of the text. This vector is then used to calculate the similarity between different schemes and recommend the most relevant ones to the farmers.

This vectorised data then can be used to calculate the similarity between different schemes and recommend the most relevant ones to the farmers.

4.3.6 Results and Analysis

On preliminary testing, the Scheme and Subsidy Awareness Module performed well in providing detailed information on various government schemes and subsidies available to farmers in Karnataka. The module is sometimes slow in responding to user queries, which may be due to the large amount of data being processed. However, the accuracy and relevance of the information provided are notable.

4.4 Multilingual System Module

4.4.1 Introduction

The Multilingual System Module is designed to provide farmers with real-time assistance and support in multiple languages. By leveraging natural language processing (NLP) and machine learning algorithms, the chatbot can understand and respond to queries in English, Hindi, Kannada, and other regional languages. This enables farmers to access information on agricultural practices, weather forecasts, market prices, and government schemes in their preferred language, making it easier for them to communicate and engage with the chatbot.

4.4.2 Literature Review

Based on the literature review, we identified that language barriers are a significant challenge for farmers in India, especially those in rural areas. Many farmers are more comfortable speaking in their regional language than in English or Hindi, which can hinder their ability to access information and support services.

The support system for farmers in India is limited, and there is a need for innovative solutions to bridge this gap. Getting hold of information on agricultural practices, weather forecasts, market prices, and government schemes can be challenging for farmers, especially those in remote areas. By providing a multi-lingual chatbot, we aim to address this issue and empower farmers to access the information they need in their preferred language.

4.4.3 Architecture

The Multi-lingual AI Chatbot is built on a modular architecture with the help of OpenAI's Realtime API. The chatbot consists of three main components: the client-side application, the relay server, and the Realtime API. The client-side application is built using React and Webpack, providing a responsive user interface for farmers to interact with the chatbot. The relay server is an optional component that can be used to enhance security and implement custom server-side logic. The Realtime API is the core component that processes user queries and generates responses in real-time.

Key Components

- **Client-Side Application**:
  - Built with React and bundled using Webpack, providing a modular and responsive user interface.
  - Includes a Realtime API Reference Client that manages the direct interaction with the Smart AI Realtime API. The client supports audio input streaming, conversation management, and tool-based function invocation.
  - WavTools Library: A custom library in `/src/lib/wavtools` manages audio recording and playback, making it easy to handle audio streams for real-time responses.
- **Relay Server (Optional)**:
  - A Node.js-based relay server (optional) can be used to enhance security by masking API keys and implementing custom server-side logic, such as filtering events or controlling access to certain tools.
  - This server is configured with a `.env` file to specify the API key and the server URL, making it simple to switch between using the relay server and directly connecting to the Smart AI API.

Key Functionalities

- **Interactive Audio and Text-Based Console**:
  - Users can initiate conversations by connecting to the Realtime API and choose between Push-to-Talk (manual) or Voice Activity Detection (VAD) modes. The VAD mode detects when users start and stop speaking, automating the flow of audio input and model responses.
  - The console enables interrupting ongoing responses, a crucial feature for controlling conversation flow in real-time applications.
- **Audio Management**:
  - Using WavRecorder and WavStreamPlayer from the WavTools library, the console allows users to capture, manage, and visualize audio input streams.
  - WavRecorder supports real-time audio input from the microphone, recording audio in chunks for transmission to the API, while WavStreamPlayer manages audio playback with control over audio buffering, frequency analysis, and playback interruption.
- **Tool Integration and Management**:
  - The console allows developers to add custom tools (e.g., `get_weather` and `set_memory`) by defining the tool's metadata and callback functions. These tools can be invoked by the model and can interact with external APIs or functions on behalf of the user.
  - This modular approach allows for easy extension, letting developers add new tools with minimal code changes, enabling experimentation with various API interactions.
- **Event-Driven Communication**:
  - The Realtime API client is built on an event-driven model, where key events such as conversation updates, interruptions, and completion are managed through event listeners. This architecture simplifies tracking and responding to user and model actions dynamically.

4.5 Results and Analysis

The Multilingual System Module demonstrated impressive capabilities in understanding and responding to user queries in Hindi, Kannada and English. This is tested with general purpose queries and also with queries that require the chatbot to use the tools provided to it at the backend.

Since it is an independent module for now, it's capabilities are limited to the tools provided to it. However, on integrating it with the rest of the modules, it can provide a comprehensive support system for farmers in multiple languages.

A glimpse of the chat interface developed till now can be seen in 4.10.

Figure 4.10: Chat interface of the Multilingual System Module

4.6 Crop Recommendation module

4.6.1 Introduction

In this module, we are using machine learning to suggest the best-suited crop for given environmental conditions. By analyzing factors such as nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall, our models determine the optimal crop recommendation. This module employs algorithms like K-Nearest Neighbors, Decision Tree, Random Forest, Naive Bayes, and XGBoost, following a structured workflow to provide data-driven insights for better agricultural decision-making.

4.6.2 Literature Review

Patel et al. (2015) demonstrated the use of Decision Tree and Random Forest algorithms for crop selection, achieving high accuracy in predictions based on soil nutrient composition. Similarly, Kumar et al. (2018) implemented K-Nearest Neighbors and Support Vector Machines to analyze rainfall and temperature data for crop recommendation, emphasizing the importance of feature selection in improving model performance.

Recent advancements in deep learning have further enhanced crop prediction accuracy. Sharma et al. (2020) utilized Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to incorporate satellite imagery and weather patterns, improving precision in yield estimation. Additionally, hybrid models combining multiple machine learning techniques have shown promising results in optimizing agricultural practices.

4.6.3 Dataset Collection

We collected a pre-made data set from Kaggle, which contains various environmental parameters such as nitrogen, phosphorus, potassium levels in the soil, temperature, humidity, pH, and rainfall. The data set provides well-structured and labeled information, making it suitable for training machine learning models. Using a standardized dataset ensures consistency and allows us to focus on model development and performance optimization rather than extensive data preprocessing.

4.6.4 Dataset Preprocessing

We begin preprocessing by checking for missing values and handling inconsistencies in the data. Feature scaling techniques such as normalization or standardization are applied to numerical attributes such as NPK values, temperature, and pH to ensure uniformity. Categorical labels representing crop types are encoded in numerical format for compatibility with machine learning algorithms. We also perform feature selection to identify the most relevant attributes that contribute to accurate predictions. Finally, the data set is divided into training and testing sets to effectively evaluate the performance of the model.

4.6.5 Results and Analysis

The results of our machine learning models highlight the effectiveness of different algorithms in crop prediction based on environmental factors. XGBoost emerged as the best-performing model, achieving a testing accuracy of 99.31%, followed closely by Naive Bayes and Random Forest, both reaching around 99.09%. These ensemble methods effectively capture complex patterns in the dataset, leading to high precision. K-Nearest Neighbors (KNN) also performed well with a 97.50% accuracy, demonstrating its suitability for this classification task. On the other hand, the Decision Tree model had the lowest accuracy, with 90% on the test set, likely due to overfitting on the training data. Despite this, it remains a lightweight and interpretable alternative.

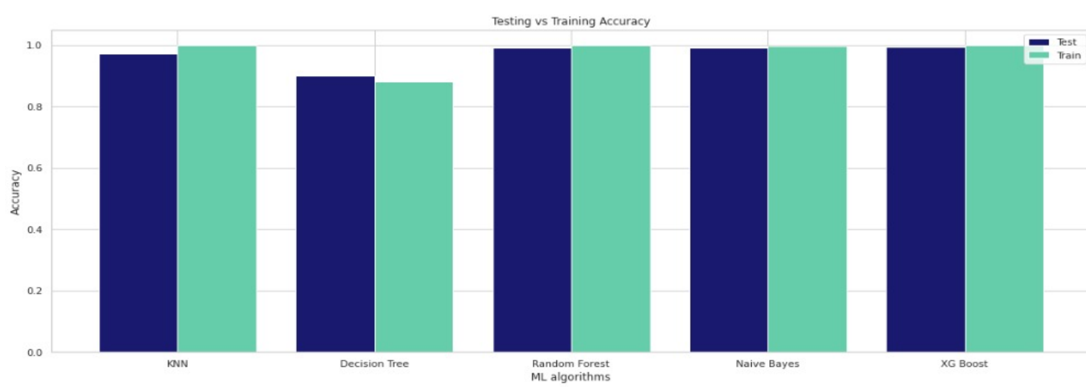

Figure 4.9: Comparison of all models

The key takeaway from this analysis is that ensemble models like XGBoost and Random Forest provide superior accuracy, making them ideal for real-world applications where precision is critical. However, KNN presents a good balance between simplicity and effectiveness, making it a viable choice depending on computational constraints. The high training accuracy observed in some models, particularly Ran-

Model	Train Accuracy	Test Accuracy
KNN	0.9886	0.975
Decision Tree	0.8818	0.9
Random Forest	1.0	0.9909
Naive Bayes	0.996	0.9909
XGBoost	1.0	0.9932

Figure 4.9: Comparison of all models

dom Forest and XGBoost, suggests potential overfitting, but their high test accuracy indicates strong generalization. Future improvements could involve fine-tuning the hyperparameters and incorporating more real-world data to further enhance the robustness and adaptability of the model.

4.7 Crop Rotation Module

4.7.1 Introduction

Crop rotation is a vital agricultural practice that enhances soil fertility, prevents pest infestations, and optimizes yield sustainability. This module aims to provide farmers with intelligent crop rotation recommendations based on their last harvested crop. Using machine learning and predefined agricultural guidelines, our system ensures that farmers make informed decisions to maintain soil health and maximize productivity.

Our model considers essential factors such as nitrogen fixation, soil moisture retention, and crop compatibility to suggest the best next crop for planting. Whether a farmer has just harvested wheat, rice, or legumes, the system provides scientifically-backed recommendations that promote sustainable farming practices. By integrating this advisory tool into a user-friendly platform, we empower farmers with data-driven insights to improve agricultural efficiency and long-term soil management.

4.7.2 Dataset collection

Government agencies such as ICAR and the National Mission on Natural Farming (NMNF) emphasize the importance of crop diversification and natural nutrient recycling to promote sustainable farming.

We compiled data from multiple government sources to ensure accurate recommendations. Key sources include ICAR (Good Agricultural Practices), NMNF (natural nutrient recycling strategies), Rainfed Area Development (RAD) (crop diversification in rainfed regions), and ICAR-IIMR (maize-specific agro-advisories). By merging insights from these sources, our system provides scientifically supported crop rotation suggestions.

4.7.3 Vectorization and Embedding

Vectorization converts text data into numerical representations, making it compatible with machine learning algorithms. In this module, we use TF-IDF vectorization to transform crop descriptions into numerical data, enabling similarity analysis for crop rotation recommendations. This approach helps identify the best follow-up crops based on soil health, nutrient requirements, and farming conditions.

The data is first tokenized, breaking down crop-related information into individual words. These words are then converted into vectors using BERT embeddings to capture contextual meanings. Vectors are processed through a neural network to generate a final vector representation of each crop. By calculating the similarity between these vectors, we recommend the next crop most suitable in the rotation cycle, ensuring improved soil fertility and sustainable farming practices.

4.7.4 Results and Analysis

The Crop Rotation Advisory Module performed well in recommending suitable follow-up crops based on the previous harvest. The module effectively analyzes crop compatibility, soil health, and nutrient requirements to provide accurate recommendations. However, there are occasional delays in generating responses, likely due to the large dataset being processed. Despite this, the accuracy and relevance of the crop rotation suggestions remain high, making it a valuable tool for sustainable farming practices.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

The development of an integrated smart agriculture application, encompassing plant disease detection, crop prediction, pesticide suggestions, and awareness of government schemes, marks a significant milestone toward technology-driven empowerment for farmers. For this experiment, **Paddy (Rice)** was selected following guidance from our advisors. Leveraging advanced machine learning models, natural language processing, and computer vision techniques, this tool addresses critical aspects of crop health management, resource optimization, and accessibility to government schemes. The incorporation of multilingual support fosters inclusivity, allowing farmers to interact with the platform in their native languages comfortably. This holistic approach is anticipated to boost agricultural productivity and enhance economic stability within farming communities by providing data-driven insights and personalized recommendations.

5.2 Future Work

In the initial phase of this project, the disease prediction module, pesticide recommendation module, scheme and subsidy awareness module, and the multilingual AI chatbot were prioritized. Future efforts will involve further fine-tuning these current modules, developing the remaining components, and integrating all modules into a cohesive and fully functional application. The ultimate objective is to create a user-friendly and practical product that can be widely adopted by farmers for increased agricultural efficiency and support.

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Timeline of the B.Tech.(IT) Major Project

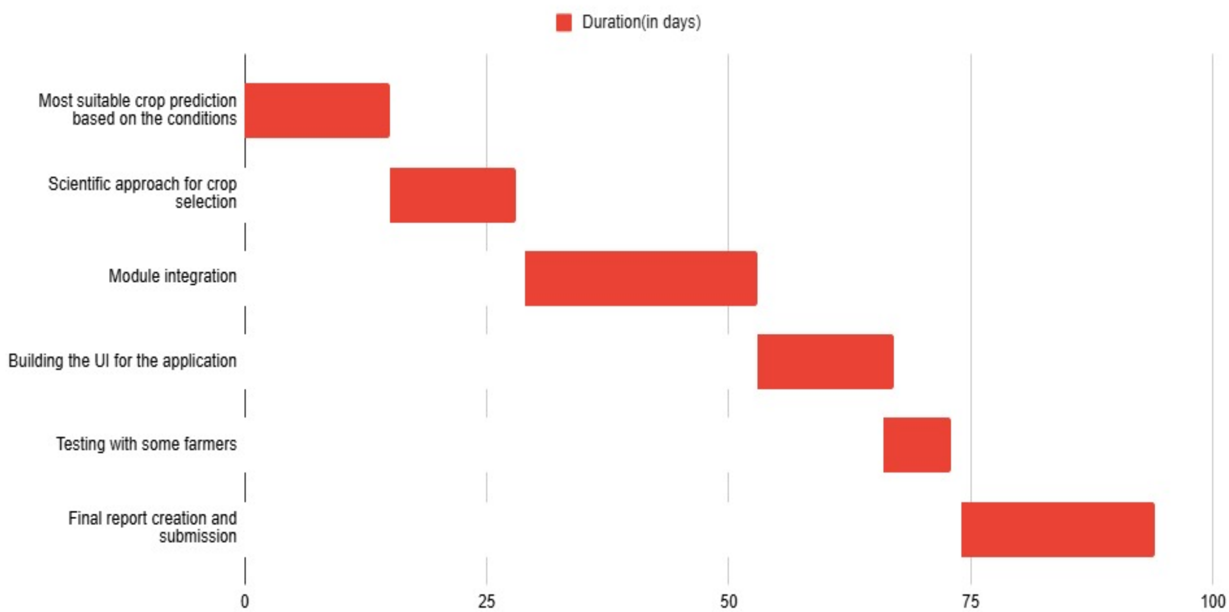

Figure 5.1: Timeline of the Project

Publication Details

This is a real time application development project, which we plan to deploy and get real farmers to use and benefit out of it.