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SCHOOL OF COMPUTER ENGINEERING AND TECHNOLOGY

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AgSolution: AI based framework for Crop Health Monitoring

The Project Report submitted to
MIT WORLD PEACE UNIVERSITY, Pune (INDIA)
in partial fulfilment of requirement for the award of degree of

Bachelor of Technology
in
Computer Science and Engineering

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CERTIFICATE

This is to certify that,
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Of BTech.(Computer Science and Engineering) have completed their project titled "**AgSolution: AI based framework for Crop Health Monitoring**" and submitted this capstone Report towards fulfillment of the requirement for the Degree of Bachelor of Technology in Computer Science Engineering of MIT World Peace University, Pune (INDIA) for academic year 2021-2022

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Declaration

We herewith submit the Project Report entitled "**AgSolution: AI based framework for Crop Health Monitoring**" to MIT WORLD PEACE UNIVERSITY, Pune (INDIA) for the award of degree of Bachelor of Technology in Computer Engineering and Technology. The work is carried out by us in the Department of Computer Engineering, MIT WORLD PEACE UNIVERSITY, Pune (INDIA), under the guidance of Prof. Pranali Kosamkar, Department of Computer Engineering and Technology.

Date:
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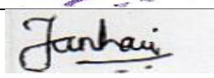
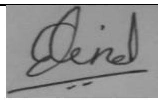
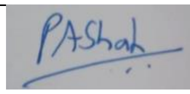
1032181707	Janhavi Chavan	
1032191776	Govind Kotecha	
1032191786	Paras Shah	

CONTENT

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

Looking forward to the recent past, during which we had been involved in. The project work, we have seen innumerable occasions on which we met seemingly indecipherable problems. In every such occasions we unhesitatingly approached our guide, who with infinite patience and awe-inspiring ease showed us the way out. It gives as great pleasure to remain deeply in debited to our project guide Prof. Pranali Kosamkar under whom we had the privilege to work the faith and the confidence shown by her in us boosted our moral and motivated us perform better in preferring this project. We also take this opportunity to express our gratitude to the Head of School, Dr. Vrushali Kulkarni for providing us with required facility for the academic achievement. We are very thankful to our friends, teaching and non-teaching staff who directly or indirectly helped us.

ABSTRACT

Agriculture plays an important role in any country's economy. It employs a huge portion of the population in addition to providing food and raw materials. The widespread presence of agricultural diseases and inefficient soil for growing crops have a significant impact on crop quality and quantity. Excessive fertilizer use, as well as a lack of fertilizer, are both common reasons for poor crop quality. It is imperative for a farmer to interpret the soil fertility level in order to achieve maximum benefits out of crop production. Crop recommendation, early disease detection, crop output prediction all effectively prevent the undesirable outcomes. Machine learning and deep learning are effective tools in the agriculture sector since they help us select which crops to produce and when to plant them. This paper describes a system that uses images to diagnose crop diseases automatically and efficiently. In addition, the system offers features such as crop recommendation, soil fertility level, and crop yield estimation based on a variety of factors such as season, crop, temperature, humidity, and soil moisture. For the same, a web application has been created. Each module featured the implementation of several algorithms, with the most accurate algorithm being selected to construct the application. Different algorithms used to train the models were Convolutional Neural Network, Support Vector Machine, Random Forest, Decision Tree, Bagging and XGBoost.All the modules have achieved the accuracy above 95%. The model's extremely high success rate makes it an excellent advisory or warning tool. This project proposes a novel approach and solution to the challenges that a farmer may encounter while cultivating crops.

CHAPTER 1

Introduction

CHAPTER 1

INTRODUCTION

1.1 PROJECT STATEMENT

To design and develop an application using Machine learning and Deep learning technology which will focus on farming technology and solve the various constraints of the Agriculture Sector.

1.2 AREA

Domain: AI, ML, Data Science, Cognitive Computing & NLP
Application Domain: Agriculture
Research Theme: Environment

1.3 PROJECT INTRODUCTION AND AIM

Agriculture is a branch of science that deals with soil cultivation, crop and fruit production, and livestock rearing. It includes the processing and distribution of plant and animal products for human use. Agriculture is one of the most significant sectors in India because it gives work to the majority of the population. There can be no country without it. Investing in agriculture is one of the finest strategies to boost growth and improve a country's standing in the global economy.

Plant disease has become a major source of concern in the agricultural sector because it invariably causes crop damage. Previously, crop disease identification had to be done by professionals or a local plant protection station. Many agricultural diseases could not be discovered on site in time due to a lack of plant protection workers, isolated locations, and insufficient transportation. People were unable to receive effective prevention advice in a timely manner due to these circumstances [4]. With the use of image processing techniques and algorithms, disease detection may be done successfully. Crop disease detection with an automated technology is advantageous since it decreases the amount of monitoring required in crop farms [7].

Many people are unaware of the importance of cultivating crops at the appropriate time and location. Also, the combined effects of a growing population, natural weather variability, soil degradation, and climate change need solutions to ensure timely and consistent crop growth and output. These requirements suggest that crop yield forecasting is more critical to global food production. This can be done by evaluating the compatibility of crops for a certain soil based on the characteristics described above by assessing weather, temperature, and numerous soil related data such as soil pH value, water availability in the region, and so on. As a result, the crop's quality and output will improve [22].

The foundation of long-term crop production is soil quality. Long-term soil health and productivity can be improved or harmed depending on what we do and how we treat our soil. Soil fertility analysis, when done correctly, reduces most of the uncertainty in fertilizer treatment while also decreasing wasteful use of important resources. Most significantly, it allows us to estimate and calculate the correct amount of nutrients to add to a soil depending on its fertility requirements.

Farmers' life has been revolutionized by modern technologies. Because agriculture is an old trade, they are first hesitant to adopt new technology. They tend to stay with tried-and-true procedures. No one can deny the impact and benefits of technology in today's world. Advances in science have made it possible for farmers to grow more crops and raise more livestock. Farmers, like all businesses, may benefit from technological improvements in order to become more efficient. Mobile apps and cutting-edge equipment boost productivity by orders of magnitude. With recent technological breakthroughs, recommender systems (RS) could be combined with machine learning approaches to help farmers make quick judgments about how to manage and control plant diseases that threaten their crops. A recommendation system is a promising artificial intelligence (AI) approach that can be used to provide meaningful item suggestions automatically and quickly in the midst of a huge number of options.

Hence, as a way to increase usability, this study investigates developing a solution that is community-oriented in design, efficient, and will bridge the digital divide between farmers and technology. We aim to develop a web application that includes an automated system for recognizing plant diseases, estimating crop production, recommending crops, and detecting soil fertility, all of which will benefit farmers and help them enhance productivity.

1.4 PROJECT SCOPE

We are developing an application that is comprised of four modules:

1.The first module is a deep learning model for disease diagnosis that uses artificial intelligence
2.The second model describes a crop recommendation system that provides suggestion for crops to grow based on the nutrient content of the soil along with some environmental parameters.
3.In the third module, we will be predicting the fertility level of soil by applying Random Forest and Support Vector Machine techniques, respectively.
4. The fourth module is that of crop yield prediction based on different parameters.

1.5 PROJECT LIMITATIONS

1. For the time being, the project can only be used for one crop; however, more crops can be added, and the app's functionality can be improved.
2.There are only four modules included, additional modules can be added in the future.

3.The technology is not compatible with drones. It can be further integrated to assist farmers in monitoring crop health and increasing yield.

1.6 PROJECT OBJECTIVES

Primary Goal

The primary goal is to design and develop an app that focuses on mobile farming technology and addresses the various limitations of Agriculture.

Secondary Goal

Create a web-based system model that can provide agricultural information from anywhere and at any time.
Mobile is used to operate the system model. Each farmer can access the information at the same time, eliminating the waste of time and energy.

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CHAPTER 2

Literature Review

CHAPTER 2

LITERATURE REVIEW

2.1 APP SURVEY

As the world's population increases, the demand for food increases proportionately. Farmers are utilizing cutting-edge technologies such as sensors, drones, intelligent irrigation, and GPS-equipped tractors to increase the sustainability of food production. According to "The Economist," farmers are being "teched up" on how to grow more sustainable and profitable crops, and as a result, food production is gradually reduced. By 2050, the world's population is expected to reach 9.7 billion people. Since then, food demand has been steadily increasing. Agriculture requires continuous and sustainable productivity growth, but with scarce resources such as water, electricity, and fertilizer, these must be used carefully to protect and sustain the environment and the soil quality of arable land. This analysis delves into 25 distinct mobile applications. These apps are focused on agricultural crops, fruits, and vegetables. It informs us of the app's benefits, drawbacks, limitations, and other features. Ricexpert app offered by National Rice Research Institute covers four major categories of rice diseases and their subcategories. This app describes nine distinct varieties of rice according to the region in which they are grown. Each of these categories has its own set of characteristics, such as release year, grain type, yield, and total duration, which are all addressed in a separate section of the app. There are six major sections, for example, weeds, nematodes, diseases, and insect pests, in which all pertinent information, as well as preventive and remedial measures, is discussed in detail. Pesticides, as well as preventative measures, are recommended. Additionally, there are features for weather forecasting, price advisory, marketing, and fertilizer calculation. As a result, the scientists have developed a methodology for diagnosing rice diseases and pests automatically [31]. The Farm calculator app maintained by Indian Council of Agricultural Research contains four sections: a fertilizer calculator, a pesticide quantity calculator, a plant population calculator, and a seed rate calculator. Each of these fields must be completed by the user. This application is universally applicable to all crops. These apps do not automatically detect disease or recommend pesticides. It is only capable of performing mathematical operations [32]. Bharat Agri app has some unique features, such as the ability to add our farm so that it can access critical field information. Our questions can be directed to the chat support system. It consists of a weather advisory system, a call support system, satellite images, and the detection of pests and diseases. This section discusses over 140 crops. A krushi book is included with detailed information on all of the crops featured in the app. It has a water testing facility, but it is a fee-based service [33]. Plant Disease Identification App detects plant diseases in 18 different fruit and vegetable varieties, as well as six agricultural crops. The authors proposed a machine learning model for disease prediction and pesticide and fertilizer recommendation. The user needs only to upload images of the damaged area. Pesticides and fertilizers are not recommended for all diseases [34]. The next app is titled as Pest and Plant Diseases. This application is not intended to diagnose disease. It encompasses all crops. This app contains information about pests and fertilizers that can be used to boost yields and prevent disease [35]. Planticus' application contains information about seven agricultural crops and two fruits, as well as their diseases. It detects disease and recommends pesticides after the user uploads a photo. There is a library section that contains information about specific crops and their diseases. This section discusses only a few crop varieties and their diseases [36]. Cropalyser is a mobile application that assesses ten distinct agricultural crops. It is not capable of real-time disease detection and makes no recommendations regarding pesticides or fertilizers. It merely provides information on the various diseases associated with a particular crop and how to prevent them [37]. Kheti Point is an app, where the user must upload an image of the diseased crop to the chat room, where an expert will analyze the disease and make pesticide recommendations. This app contains data on all crops. The only restriction is that you must take and upload a picture each time. Due to the lengthy nature of this procedure, the image may occasionally be blurred [38]. Agri Doctor is the app that covers a few different varieties of fruits, vegetables, and agricultural crops, as well as their diseases. The app contains a single section devoted to the latest equipment and instructions on how to use it. These applications are limited to a few crop varieties [39]. Next app is Scouting. This app operates similarly to Agri Doctor. The only drawback is that only a limited number of crop varieties are covered [40]. Agri Central is an app, which is similar to Scouting. It includes a weather report and a calendar for tracking completed tasks. This will assist you in staying organized and on top of all tasks and important dates [41]. Agri AI is an application that supports a limited number of agricultural crop varieties [42]. The e-Mausam Krishi app is maintained by the government of Haryana. App include a plethora of features and are applicable to all crops. Additionally, to crop-specific pathogens. It contains detailed information on crops, diseases, preventive measures, and general recommendations for disease management. Weekly crop updates are provided. There is a source for a contact number for scientists. It does not assist in real-time disease detection [43]. AgriSetu is an application that provides information on a variety of fruits and agricultural crops. It includes a calendar outlining the crops grown in each month. Additionally, this app includes a soil-related feature [44]. Plantix app covers all crop-specific diseases and categorizes them according to the stage at which they manifest. Fertilizers are recommended based on the plot's size. The app is only compatible with a limited number of crop varieties [45]. Pacific Pathogens of pests and weeds app includes fact sheets on every disease, weed, and mite. However, the app does not allow for user interaction in order to provide specific disease information [46]. The Kisankraft App discusses a variety of crops. It provides a weather forecast and calculates fertilizer dosages using the user-supplied NPK values. There is a section devoted to renting tools and machinery. This app does not contain all available information on diseases [47]. Agrostar is another app that covers all crops and only provides expert advice on diseases or pesticides over the phone. This is the sole constraint that requires us to consult experts for each and every query [48]. AgroAi app covers two fruits and six agricultural crops. Apart from the other apps, this one includes a soil fertility test feature that requires the user to enter a pH value and displays the results. To diagnose a disease, the user must upload an image, and the app will suggest a treatment. Not all crops are covered here, and not all results are displayed [49]. Onesoil's Scouting app is a farming scouting tool. All crops are covered here, as the field can be located on a map and variable fertilizer rates determined. However, while working on the map, it lags and eventually stops working [50]. The Agrio app provides information on two fruits and four agricultural crops. The user uploads an image of the crop, which is then diagnosed by experts and recommended pesticides and fertilizers [51]. Leaf doctor is the next app. The app’s primary objective is to ascertain the health of diseased leaves. The only restriction is that suggestions must be submitted via email [52]. Plantify Dr focuses on a few agricultural and fruit-related topics. To detect the disease, it is proposed that a machine learning model be used. It makes no recommendation regarding the use of pesticides or fertilizers [53]. Crop Diagnosis app covers only three crops. The app suggests a diagnosis via chat, and users can then take additional measures to protect crops [54]. The Purdue Tree Doctor app which is offered by Purdue University covers over 60 trees and crop-specific diseases. It makes recommendations regarding pesticides and treatments for specific diseases. Pesticides are not recommended [55]. These were the different apps evaluated which highlighted distinct characteristics of each app along with their shortcomings.

2.2 LITERATURE SURVEY

Over the course of the past ten years, a substantial quantity of research work has been carried out in the field of agriculture. The majority of the early methods for identifying crop diseases are manual. These approaches are mostly used by farmers or other related specialists to diagnose and identify crop illnesses in the field. When it comes to identifying crop diseases, these methods are extremely reliant on the personal experience of the farmers or relevant experts. These methods suffer from a number of issues, the most notable of which are a high rate of recognition errors, acute personal subjective awareness, and low recognition efficiency. Improvements in crop disease identification have been made possible by recent advances in image processing technology and their subsequent implementation in the agricultural sector. In this section, we will cover the research that has been carried out employing popular DL and ML architectures for the purpose of recognising and categorizing diseases, predicting the Yield and Recommending Crops based on different climatic or meteorological factors. This analysis delves into 21 different papers which highlights the technology used, functionality provided by the app. A Lakshmanarao et al. have proposed the system for detection and classification of plant diseases wherein they have applied Convnets algorithm, and achieved the accuracy above 95% for all the crops [56].M Sowmiya et al. have performed the survey of different papers wherein machine learning algorithms are used along with image processing techniques. They have proposed a deep learning algorithm for detection of diseases based on the research gap. In the future web apps can be deployed which will consist of these models, so that farmers can use it [57]. Ng, Hui Fuang et al have applied Deep learning and Faster-RCNN algorithms for disease detection which have achieved accuracy of 97.9%. The Web app of the same is deployed [58]. Mengji Yang et al have proposed a technique where the Resnet50 algorithm is used along with transfer learning for automatically detecting diseases in the web app which have achieved the accuracy of 92% [59]. Blessing K. Sibanda et al have conducted a survey on user reviews which consist of 19 different themes.They are divided across different qualities . The users have requested to add more functionalities in the app [60]. T. Kavitha et al have proposed a system that recommends fertilizer and detects disease which helps in increasing the crop productivity. Random forest and Deep learning techniques have been applied. There is no app available for the same, in future the work can be extended to prepare a web app which will help the farmers [61]. Mayuresh Deodhar et al have designed the system which consists of two parts. In the first part based on different conditions crop is recommended and Bee hive is used which will show the output. In the second part the disease of crops is detected. Bee Hive clustering approach improves the usability of system [62]. Venkanna Udutalapally et al have implemented a real time solution where solar sensor nodes are used along with a camera module which can monitor the field. The system has achieved 99.24% of accuracy [63]. Folasade Olubusola Isinkaye et al have proposed a user-friendly web app which detects plant diseases. ANN along with KNN algorithm is applied [64]. Avnika Shah et al have designed the system which will not only predict the crop yield but also extract different trends using NDVI. XGboost algorithm which has achieved 96% of accuracy [65]. Mummaleti Keerthana et al have implemented crop yield prediction models using different machine learning algorithms among which adaboost has achieved highest accuracy which is around 95.7%. In future a web app can be created for the same [66]. Manish Kumar et al have proposed the multi layered perceptron model which not only classifies but detects the diseases. The average accuracy achieved is above 98% for all crops. The system is feasible and affordable [67]. Devdatta A. Bondre et al have implemented a system which predicts the crop yield using machine learning models Random Forest and Support Vector Machine. Support vector machine has achieved 99.47% of accuracy, further Smart System can be developed for the same [68]. Dhruvi Gosai et al have designed the system wherein they have combined IOT and ML for soil testing with the help of sensors. Among all the algorithms XGboost has achieved the highest accuracy of 99.31%. In future more attributes can be added in the dataset which can be further trained and user friendly mobile apps can be developed [69]. R. Deepika Devi et al have proposed an IOT system for plant disease detection which monitors different environmental parameters and makes predictions. The overall accuracy achieved is 99% [70]. D. Devi1 et al have proposed the technique which combines SVM and CNN algorithm. The fruit is then diagnosed and the amount of pesticides is predicted from the image. The accuracy achieved is 90% [71]. Jagadish Kashinath Kamble has developed a mobile app for plant disease detection using image processing [72]. Kaushik Kunal Singh has built disease detection models using AI. They have used their own dataset which is collected from 7 different farms. The model has achieved 95% of accuracy [73]. Michael Gomez Selvaraj et al have developed an AI based pest detection system using DCNN. The system has achieved accuracy between 70-90% [74]. Heamin Lee et al have designed an IOT system to detect when the pest can appear and how it can be prevented. In future work more attributes can be used [75]. Heamin Lee et al have designed a multidimensional Resnet model for crop disease detection along with IOT. The accuracy can be improved in future by improving the image quality [76].

2.3 SURVEY OF PAPERS ACCORDING TO ALGORITHMS USED

Machine learning

The approaches used in agricultural machine learning are drawn from the learning process. These ways must be learned through experience in order to complete a certain goal. Machine learning is used in agriculture to boost crop output and quality. Nikita Yadav **et al.** have reviewed different machine learning techniques like Decision Tree, Random Forest, Image Preprocessing for detection of leaf diseases. The proposed system Suggests the pesticides for particular disease [24]. Digital agriculture is growing in popularity, as it provides a safe method for increasing agricultural productivity while minimizing environmental impact. Modern agriculture collects data using a range of sensors to gain a better understanding of the environment, which includes crop, soil, and weather variables. These facts will enable us to make quick, result-oriented decisions. Abhishek Shah **et al.** have proposed a weather-based forewarning pest prediction model. It detects different pests for a particular crop. In future the system can be developed as an end-to-end product using a prototype [25]. Farmers can forecast harvest yields, evaluate crop quality, detect agricultural diseases or weed infestations, and identify plant species with the use of sensors mounted on drones and machine learning digital apps. Spoorthi S. **et al.** have developed a Freyr drone which aims to reduce the work of farmers and complete the task in less amount of time. The drone is used for spraying pesticides [21]. Prof. Swati D Kale et al., have proposed a UAV model for spraying chemicals. This model works on the feedback provided by Wireless Sensor Networks which is further deployed on the crop field. They have developed an algorithm for adjusting the drone according to wind [22]. In agriculture, machine learning techniques such as regression, Kmeans, KNN, random forest, and SVM can be employed. Because the accuracy levels of various machine learning algorithms vary, the initial step of selecting an algorithm to use is critical. Numerous factors affect the performance of selected algorithms, including the size of the data set used, experimental noise, and data collection errors, to mention a few.

Support Vector Machine: The SVM algorithm is most often used for classifying agricultural items according to their size, texture, form, variety, colour, and quality. SVM outperforms other machine learning approaches in terms of classification performance in general. The primary objective of SVM is to find the optimal hyperplane for linearly separating data points in two components while optimizing the margin. SVM may be used to analyze and segment images of grains, fruits, and vegetables, as well as other agricultural products. Additionally, it can be used to categorize pests and crop coverage. Dr. Kiran Kumar Gurral **et al.** have proposed a disease diagnosis model which identifies disease at an early stage. The work can further be extended to detect the diseases using hybrid techniques [6]. Muhammad Junaid **et al.** have proposed a cloud-based system on which different activities related to agriculture are monitored and analyzed by agricultural experts. SVM algorithm is used to classify the data. The work can further be improved by working on precision agriculture and other critical factors [10]. Ms. Supriya shinde **et al.** has proposed a system which predicts crop diseases using IOT and SVM. Parameters like temperature, humidity, rainfall, light intensity are taken into consideration. The work can further be extended to build an app which could be useful for farmers [14]. Monzurul Islam **et al.** have presented an approach wherein they have combined image processing and SVM to detect the plant leaf disease of over 300 images .95% of accuracy is achieved using SVM classifier [15]. Debasish Das **et al.** has implemented a framework for detection of diseases. For classification purposes three different algorithms are used which are SVM, Random Forest and Logistic Regression. SVM outperforms the other two algorithms. This particular model can be used in real life applications [27].

K-Nearest Neighbour*:* The KNN approach is a data mining technique that is often considered to be one of the top five. By selecting the k closest data points to the new observation and selecting the most common class among them, the method identifies which points from the training set are similar enough to be included for predicting the class for a new observation. This is where the k Nearest Neighbours' algorithm gets its name. Crop Yield Prediction is one of the applications of this technology. M.P. Vaishnave **et al.** has designed an application for detection of groundnut leaf diseases. Four different groundnut diseases are categorized here. KNN algorithm is used here which increases the accuracy of the model. In future extra classifiers can be added which will decrease the false classification [28].

Random Forest: A random forest algorithm is used to solve classification and regression problems. It solves complex issues through the use of ensemble learning.

The Random Forest method produces decision trees from several data samples, forecasts data from each subset, and then votes on the system's best alternative. It is used to predict crop yield and categorize agricultural crops. R. Deepika Devi **et al.** has presented an IOT system along with Random Forest algorithm to detect and classify the disease in banana plants. Different environmental parameters like temperature and soil moisture are taken into consideration. The model has achieved the accuracy of 99% [2].

Regression: Regression analysis is used to estimate the relative strength of a dependent variable and an independent variable. Regression Analysis is a frequently utilized technique in research to ascertain the relationship between the three variables (AUC, AR, and FPI) and their impact on crop output. The dependent variable is crop yield, while the independent variables are AUC, AR, and FPI. Regression analysis is used to determine the relationship between a dependent variable and an independent variable, for example, the effect of AUC, AR, and FPI on yield. It is used to forecast crop yields. Kumar **et al.** have proposed a recommendation system which detects the diseases and recommends pesticides. It also gives suggestions about which crop to grow. The model has achieved 86% of accuracy [17].

K Means: The k-means algorithm is used to cluster the agriculture data. The K value selection is critical in the k-mean algorithm. Numerous ways are used to determine the number of cluster values (k-value). Determining a suitable initial centroid is critical when using the k-means approach. It is used to predict agricultural productivity and soil fertility. Mugithe **et al.** have proposed an application for identifying leaf disease. It employed the K-means clustering technique in two ways: through the graphical user interface, where it achieved an accuracy of 95.1613 percent, and in real-time, where a buzzer alerts the farmer if a disease is detected [4]. Tete **et al.** proposed a model which outlines numerous segmentation approaches for determining the presence of various plant diseases. Additionally, this research studies categorization approaches for plant diseases [7]. Vijai Singh **et al.** has proposed an algorithm which automatically classifies and detects the diseases. The algorithm is applied on four agricultural crops among which bean crop achieved 92% of accuracy [16]. Despite the fact that the k-means clustering algorithm requires an a priori determination of the number of cluster centers, this strategy is more successful than thresholding and gives the best results when dealing with diverse data sets.

After analyzing multiple machine learning models, it is noticeable that most researchers used SVM even though all models have given adequate accuracy. Along with SVM, the K-Means algorithm is the other algorithm which is used by most of the researchers.

Deep Learning

Crop management is critical for improving crop quality. Drones are increasingly performing critical duties in agricultural crop management, including crop monitoring, field scanning, and more. Deep learning techniques such as CNN, RNN, ANN, Resnet, and Inception can be employed in agriculture. Because the accuracy levels of various deep Learning algorithms vary, the initial process of selecting an algorithm to use is critical. It is crucial to detect and recognize diseases in crops at an early stage in the agricultural industry. Sammy V. Militante et al. has developed a deep learning-based system to detect and recognize diseases in several plant varieties [1]. Lili Li et al. have studied the scientific advancement of deep learning technology in the field of crop leaf disease detection that has been done in recent years. One of their primary learnings is that better resilience deep learning models are required to adapt to diverse datasets [11]. Tanha Talaviya et al. look at how artificial intelligence can be used in agriculture for irrigation, weeding, and spraying with the use of sensors and other devices integrated in robots and drones. These technologies reduce the amount of water, pesticides, and herbicides used, preserve soil fertility, aid in the efficient use of manpower, and increase productivity and quality. They have conducted a survey to look at the work of a number of researchers in order to acquire a quick overview of the present state of automation in agriculture, including weeding systems using robots and drones [20]. Solemane Coulibaly et al. have suggested a method for constructing a mildew disease diagnostic system in pearl millet that combines transfer learning and feature extraction [26]. Demonstrations show that using a transfer learning approach for image recognition provides a quick, low-cost, and easy-to-use solution for detecting digital plant diseases. Amanda Ramcharan et al. has used transfer learning to train a deep convolutional neural network to identify three diseases and two types of pest infestation using a dataset of cassava disease images captured in the field in Tanzania [29]. Deep learning techniques such as CNN, RNN, ANN, Resnet, and Inception can be employed in agriculture. In smart agriculture, deep learning algorithms are used to monitor the temperature and water level of the crops. Additionally, farmers can monitor their fields from any location on the planet. This intelligent agriculture system powered by AI is incredibly effective. Deep learning has a plethora of applications in agriculture [30].

Artificial neural networks: ANN are used to model nonlinear situations and predict output values using training data. Recent years have seen a substantial increase in the usage of ANNs for crop production prediction. ANNs were more effective at explaining yield variability than other techniques [20]. Jagadish Kashinath Kamble ***et al.*** has presented an image processing technique based on ANN for detecting plant diseases so that farmers can take measures to cure them timely [8]. *CNN.* D. Devi et al. have utilized CNN and SVM for building a model which detects diseases in fruits. To get the information about the presence of pesticides in real time, few sensors, Arduino and a Wi-Fi module were used [3]. Pushkara Sharma et al. have developed an artificial intelligence-based autonomous plant leaf disease detection and classification system that allows for quick and easy disease detection, classification, and treatment. They used logistic regression, KNN, SVM, and CNN as the system's classifiers. CNN has been found to outperform all other algorithms [5]. Kaushik Kunal Singh devised a real-time diagnosis using CNN for cloud-based image processing. To achieve higher accuracy, the model constantly learns from user-submitted photographs and expert suggestions [9]. Michael Gomez Selvaraj et al. have created an AI-based banana disease and pest detection system using DCNN to assist farmers in cultivation of bananas. Their study revealed that the DCNN is a reliable and simple-to-implement technique for detecting banana disease and pests [12]. Melike Sardogan et al. have developed a tomato leaf diseases detection and classification method based on CNN with Learning Vector Quantization algorithm. The proposed approach effectively recognizes four different forms of tomato leaf diseases. Varying filters or different sizes of convolutions can be employed to increase recognition rate in the classification process [13]. Pranali K. Kosamkar et al. have suggested a system that uses Tensor flow technology to do preprocessing and feature extraction of leaf pictures, followed by CNN for disease classification and pesticide recommendation. To train the model, they have employed CNN with different levels (three, four, and five layers) and an android application as the user interface [23].

Residual neural network: ResNet is a type of artificial neural network (ANN) that is inspired by the cerebral cortex's pyramidal cells. Typical ResNet models employ double- or triple-layer skips with nonlinearities (ReLU) in between and batch normalization. The Resnet model can be used to identify crop diseases and make pesticide recommendations. Yong Ai et al. employed the Inception-ResNet-v2 model, which was built utilizing deep learning theory and CNN, to automatically identify agricultural illnesses. They have also integrated their model with an app for detecting agricultural diseases and insect pests, as well as providing relevant advice. The model can be expanded for more crop species in the future [18]. Wei-Jian Hu et al. utilize deep learning and IoT technology to develop a comprehensive understanding of crop disease recognition. Apart from identifying the disease, it also distinguishes between disease stages. On all metrics, the MDFC–ResNet model outperforms the other models. It has the highest average accuracy, the widest range (from zero to one), and the highest precision, recall, and F1 values [19].

Inception V3: Inception v3 is a very well-known image recognition model that has been shown to perform significantly better on the ImageNet dataset than previous versions. It can be used to identify disease and pests. Tejas Pandit et al. addresses inception networks, their imitations, and the difficulties encountered by some of the architectural schemes utilized in inception networks. The performance of various inception network versions was evaluated. They found that these networks are a promising area of research, and that various models integrating these variants performed exceptionally well in picture classification difficulties [30].

After analyzing multiple models, it is noticeable that most researchers used CNN even though all models have given adequate accuracy. When compared to machine learning algorithms, deep learning models have demonstrated to be more accurate.

CHAPTER 3

PROJECT REQUIREMETS

CHAPTER 3

PROJECT REQUIREMENTS

3.1 SOFTWARE REQUIREMENTS

• Python

Python provides code that is both concise and readable. Machine learning and AI are based on sophisticated algorithms and flexible workflows, while Python's ease allows developers to design dependable solutions. Rather than concentrating on the technical subtleties of the language, developers can devote all of their attention to resolving an ML problem. Version 3.9.1 of python has been used.

• TensorFlow

TensorFlow is a Python library developed and distributed by Google for fast numerical computation. As a basis, TensorFlow may be used to build Deep Learning models directly, or with wrapper libraries that make the process much easier. TensorFlow version 2.5.0 is used.

• PHP

Server-side scripting language PHP (PHP Hypertext Preprocessor can be used to build dynamic web pages that interact with databases. It's a widely used open-source programming language for building online applications that can be included into the HTML code. In PHP, the scripting code is run on the servers, which builds HTML that is transmitted back to the client.

• HTML & CSS

Websites are built using HTML and CSS, two of the most important technologies in the world of web design. The core of the page is provided by HTML, while the (visual and auditory) layout is provided by CSS for a number of devices.

• Xampp

Prior to releasing the website to the main server, XAMPP enables a local host or web service to test its website and clients on desktops and laptops. Platform for testing and verifying the operation of projects on the host's own system provides a suitable environment.

3.2 HARDWARE REQUIREMENTS

- Windows/MAC laptop
- Sensors

CHAPTER 4

SYSTEM ANALYSIS AND

PROPOSED ARCHITECTURE

26
26

CHAPTER

SYSTEM ANALYSIS AND PROPOSED ARCHITECTURE

As a result of farmers' inability to detect the disease type in its earliest stages, the agriculture industry experiences a significant decline in productivity and crop losses annually. Observations of leaves by a farmer are frequently unable to recognize the disease type, necessitating the assistance of an expert. These losses have a significant influence on productivity and, consequently, the farmer's way of life. The proposed model is a web application that consists of an automated system for identifying plant diseases, predicting the crop yield, recommending crops, and detecting the fertility of the soil that will assist farmers and help to increase productivity. The following are the modules involved in the Web App:

1. Disease Detection Module
2. Crop Yield Prediction Module
3. Crop Recommendation Module
4. Soil Fertility/Infertility Detection

4.1 SYSTEM ARCHITECTURE

The suggested model is a web application that includes an automated method for recognizing plant diseases, estimating crop yield, recommending crops, and detecting soil fertility. These will benefit farmers and help them boost productivity. Figure 1 shown below gives an overview of the complete system.

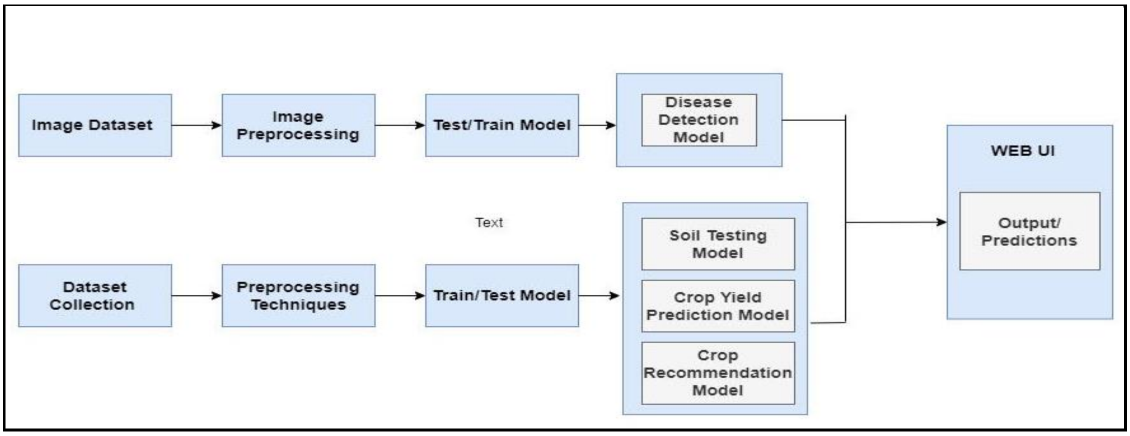

Fig. 1. System Architecture

4.2 CROP YIELD PREDICTION

Based on various parameters such as state name, season, temperature, humidity, soil moisture, area, production, and crop, this module will aid the farmers in estimating crop yields. The below figure shows the proposed system for crop yield prediction.

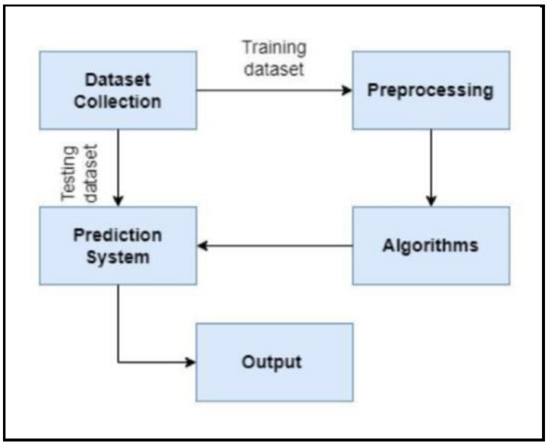

Fig. 2. Crop Yield Prediction Module

4.3 Disease Detection Module

Figure 3 shows the architecture of a disease detection module that allows farmers to quickly identify crop diseases and apply precise management actions to avoid crop failure.

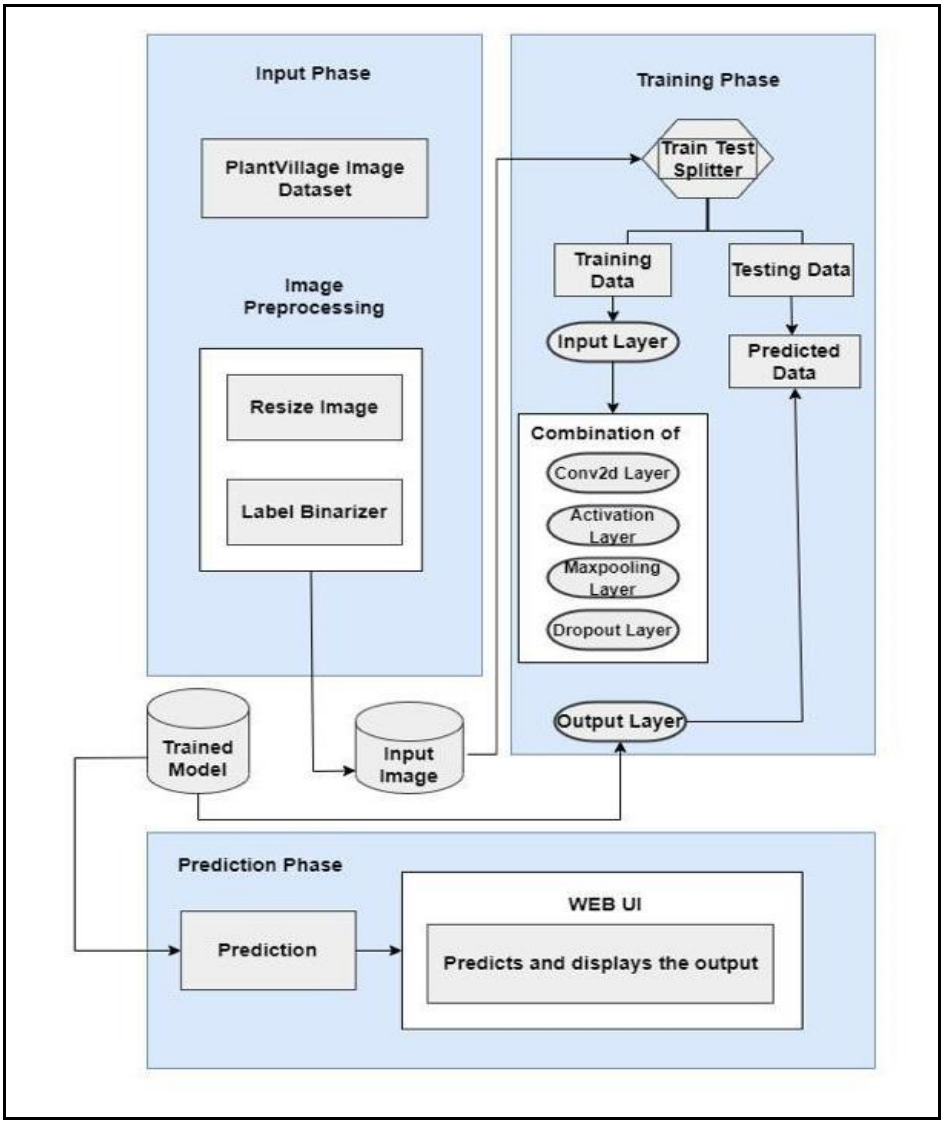

Fig. 3. Disease Detection Module

4.4 Crop Recommendation Module

Based on various parameters such as N, P, K, temperature, pH, and humidity, this module will recommend a crop most suitable to be grown based on entered values. The suggested crop recommendation system is depicted in the diagram below.

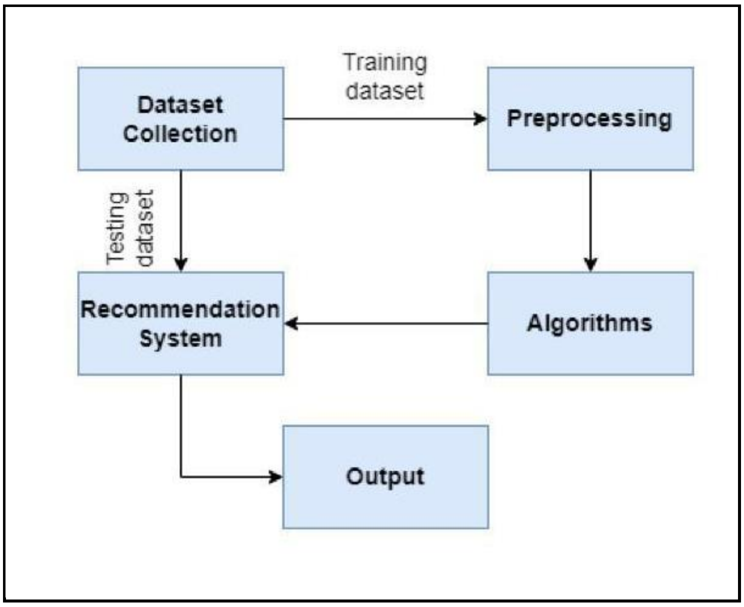

Fig. 4. Crop Recommendation Module

4.5 Soil Fertility-Infertility Detection Module

Predicting the fertility of the soil will help to alleviate some of the challenges that farmers must contend with and will serve as a conduit for providing agriculturalists with the evidence that is necessary to achieve higher yields. The proposed system for determining soil fertility is given below.

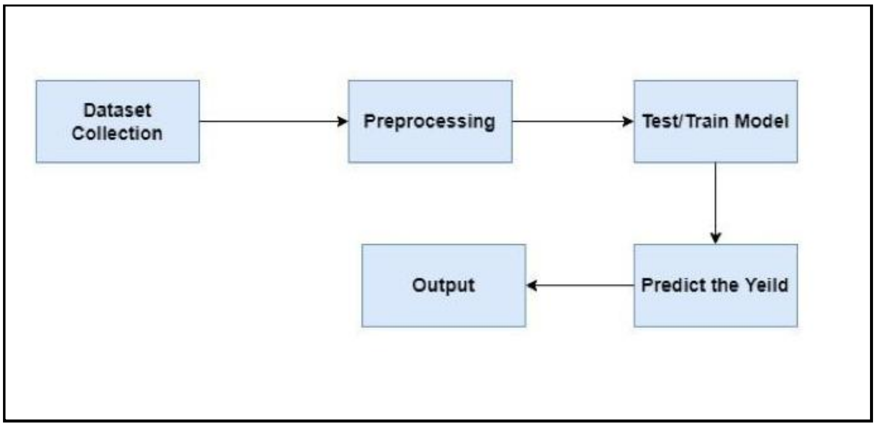

Fig. 5. Soil Fertility-Infertility Module

CHAPTER 5
PROJECT PLAN

CHAPTER 5

PROJECT PLAN

5. Project Plan

It is critical to have a well-thought-out project strategy to avoid wasting time and resources. For the same reason, we've used a Gantt Chart to visualize our strategy. Figure 6 displays a list of completed tasks as well as the amount of time it takes to complete each activity.

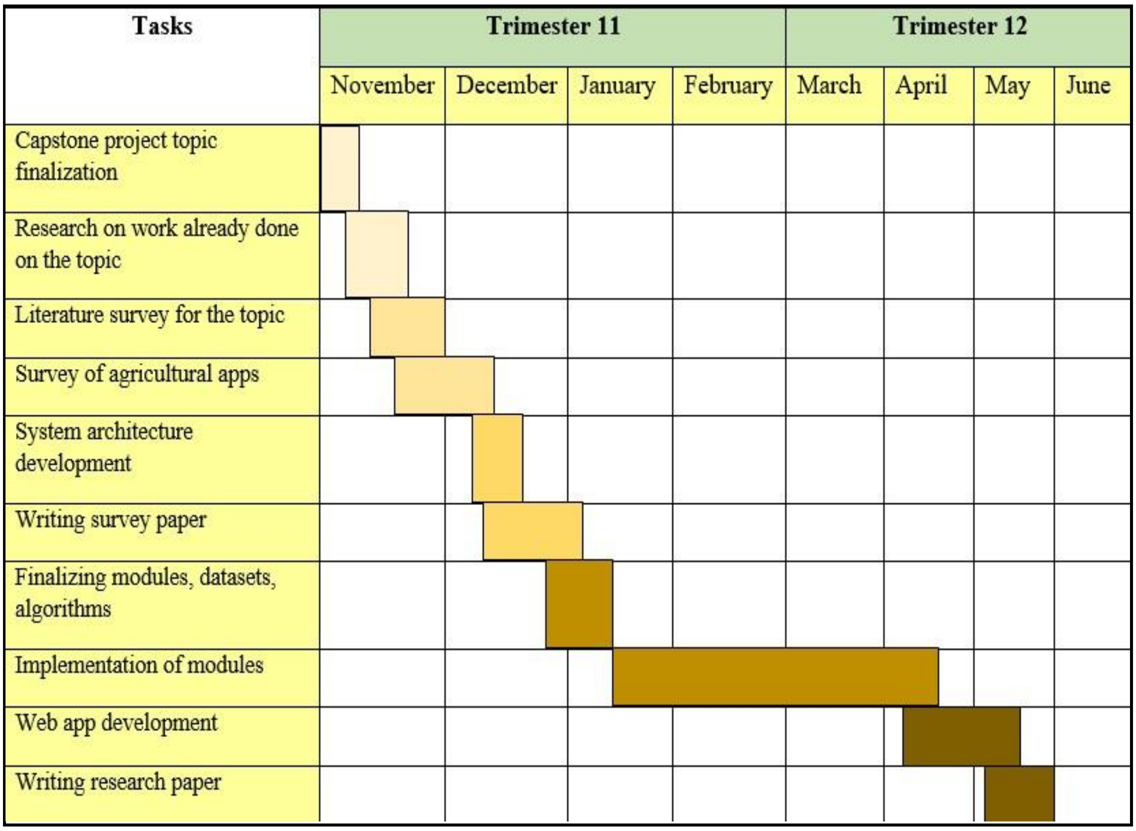

Fig. 6. Complete Project Plan

32

CHAPTER 6
IMPLEMENTATION

CHAPTER 6

IMPLEMENTATION

A. Disease Detection Module

6.1. Methodology

(1) Image acquisition is the very first step that requires capturing an image with the help of a digital camera.

(2) Preprocessing of input image to improve the quality of image and to remove the undesired distortion from the image. To increase the contrast, Image enhancement is also done.

(3) In the infected clusters, inside the boundaries, remove the masked cells.

(4) Obtain the useful segments to classify the leaf diseases. Segment the components using inception, ResNet and CNN algorithm.

(5) Classification of disease

6.2. Algorithm

6.2.1 CNN

In neural networks, a convolutional neural network is one of the techniques for image classification and recognition. It's made to process data over numerous levels of arrays. This sort of neural network is employed in image identification and facial recognition applications. The main distinction between CNN and other neural networks is that CNN uses a two-dimensional array as input. And, unlike other neural networks, it works directly on images rather than focusing on feature extraction. The figure given below shows the architecture of a CNN [77].

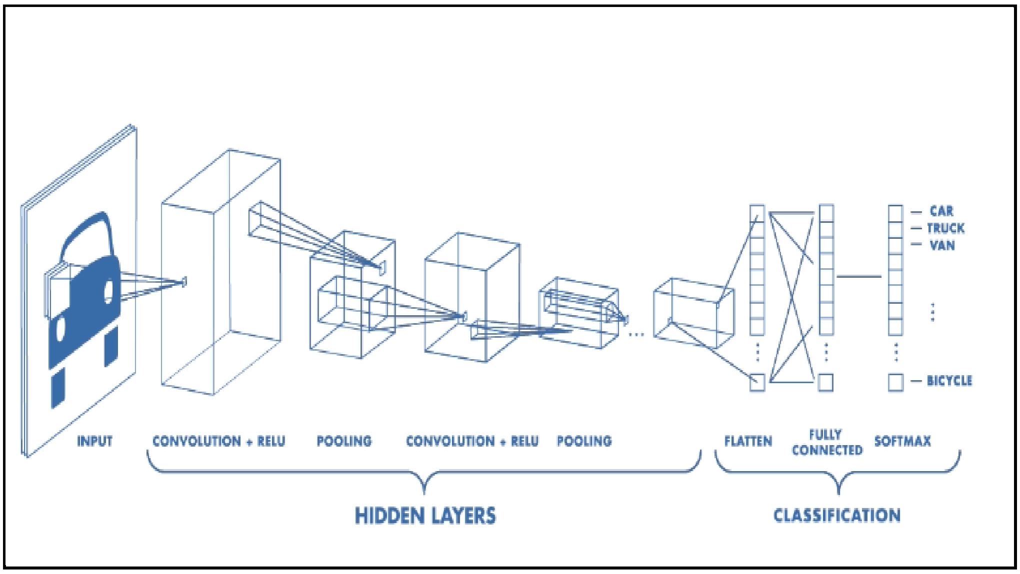

Fig. 7. CNN Architecture

6.2.2. Inception Network

Inception-v3 is a 48-layer deep convolutional neural network. Several strategies for improving the network have been proposed in an Inception v3 model to loosen the constraints for faster model adaption. Factorized convolutions, regularization, dimension reduction, and parallelized calculations are among the approaches used. If an Inception Network is changed, special care must be taken to ensure that the computational advantages are not lost. As a result, because of the uncertainty of the new network's performance, adapting an Inception network for multiple use cases becomes an issue.

6.2.3. ResNet

When training deep networks, there comes a point where the accuracy reaches a saturation point and then rapidly degrades. The "degradation problem" is what it's termed. This demonstrates that not all neural network topologies are created equal. To address this problem, ResNet employs a technique known as "residual mapping." Instead of assuming that every few stacked layers will suit a desired underlying mapping, the Residual Network allows these layers to fit a residual mapping explicitly.

6.3. Dataset

The model that will detect and categorize the corn disease is put through its paces by testing and training on the dataset shown below. CNN, Resnet, and the Inception algorithm were utilized in the construction of the model. The dataset that was utilized was the Plantvillage dataset, which included images of corn with four distinct diseases. These diseases were referred to as Cercospora leaf spot Gray leaf spot, Common rust, healthy, and Northern Leaf Blight. It consists of both test and train images.

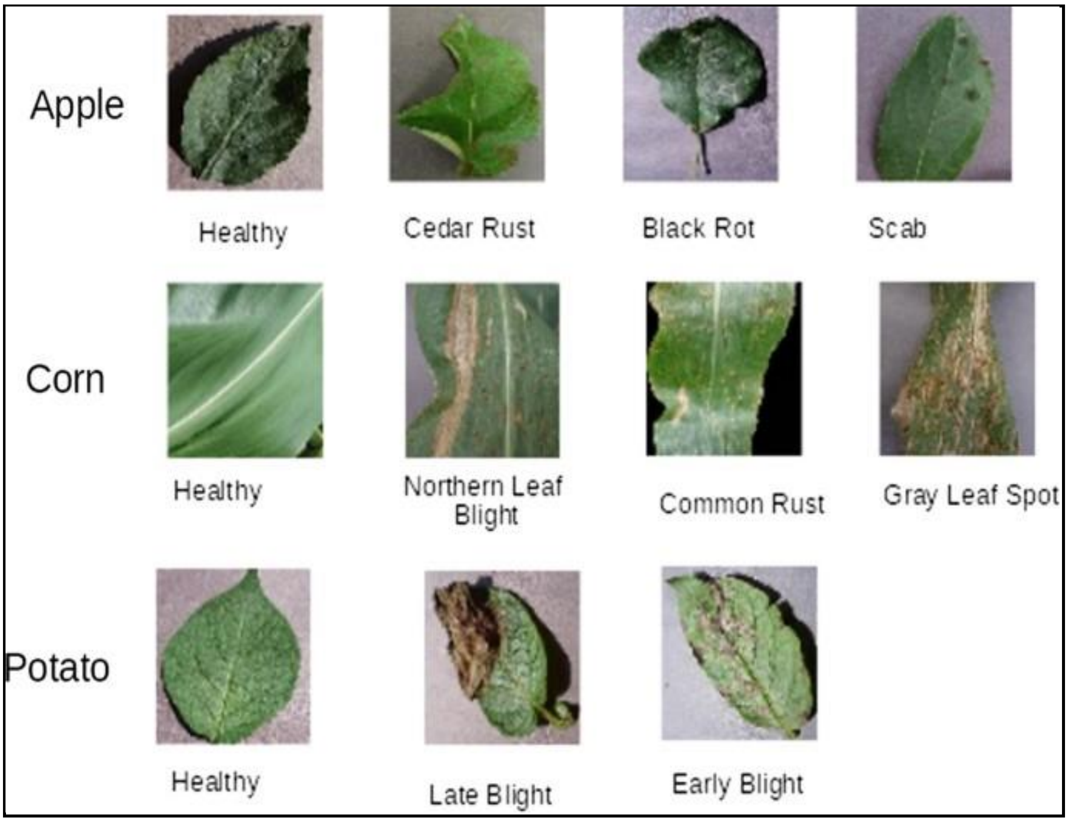

Fig. 8. PlantVillage Dataset

B. Crop Recommendation Module

6.1. Methodology

The crop dataset includes samples of data pertaining to crops in addition to the features of those crops. pH, nitrogen, phosphorus, potassium, temperature in degrees Celsius, relative humidity, and crop labels are the various parameters of soil. A wide variety of crop types are collected and arranged into categories by using the numerous crop criteria. The second component of the system being considered will assist farmers in determining what kind of crop will be most successful in a given soil by analyzing the nutrients that are already present in that soil. After collecting the dataset Preprocessing is applied to check the missing values and clean the data. Then the X and Y variables are defined. The dataset is then split into train and test data on which the models are trained and tested. After developing a web app via which the user will enter the soil and crop characteristics and then mapping both the data obtained from the user and the data samples, the final product is presented. There are five different machine learning algorithms that are utilized to locate an input into a crop class. The permissible crop for the actual soil parameter is returned by the dataset as a result of mapping. Through the use of a Web user interface, the results that were acquired are presented to the user or farmer. The data sample contains the pH, N, P, and K values, as well as the temperature in Celsius, the relative humidity, and the crop label.

6.2. Algorithms

6.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm or model which can be used for classification and as well as for regression challenges. However, we mainly use it in classification challenges. SVM is generally represented as training data points in space which is divided into groups by an intelligible gap which is as far as possible. SVMs can accurately carry out a non-linear classification using a technique called the kernel trick, which is indirectly mapping the inputs into high-dimensional feature spaces.

6.2.2. Decision Tree

The Decision Tree algorithm belongs to the category of supervised learning algorithms, and we utilize it, along with other algorithms in that category, to solve a variety of regression and classification problems. The primary goal of a Decision Tree is to create a training prototype that can be used to predict the class or value of target variables by learning decision rules derived from past data (training data).

6.2.3. Bagging algorithm

Bagging classifier is an ensemble meta-estimator that fits base classifiers to random subsets of the original dataset and then aggregate their individual predictions (either by voting or average) to generate a final prediction. By integrating randomness into the construction technique of a black-box estimator (e.g., a decision tree), such a meta-estimator may often be used to lower the variance.

6.2.4. Random Forest

Random Forest is a classifier that combines a number of decision trees on different subsets of a dataset and averages the results to increase the dataset's predicted accuracy. Instead of relying on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority votes of predictions. The greater the number of trees in the forest, the more accurate it is and the problem of overfitting is avoided.

6.2.5. XGBoost

Gradient Boosted decision trees are implemented in XGBoost. Decision trees are constructed sequentially in this approach. In XGBoost, weights are very significant. All of the independent variables are given weights, which are subsequently fed into the decision tree, which predicts outcomes. The weight of factors that the tree predicted incorrectly is increased, and these variables are fed into the second decision tree. These various classifiers/predictors are then combined to create a more powerful and precise model. It can be used to solve problems including regression, classification, ranking, and user-defined prediction.

6.3. Dataset

The dataset is put to use in both the testing and training of the prediction model that was constructed with the assistance of machine learning methods. This dataset includes seven attributes, which are the pH, N, P, K, temperature (C), crop label and

humidity. The dataset is part of a survey which was carried out in pune.The survey was done for total 10 crops including chana, chikoo, coconut, corn, jackfruit, mango, Fenugreek, Custard apple, and sugarcane. Two farms were selected for collection of data. 4 in 1 PH meter was used to take the readings of Ph value, Temperature, and Humidity and for NPK values Agrinex was used. There are a total 1019 instances in the dataset. Below the given table shows a few instances of the dataset.

Table 1. Dataset instances for crop recommendation module

N	P	K	pH	temperature	humidity	label
26	24	38	5.6	20	87	chikoo
59	40	29	6.6	23	77	wheat
56	44	50	6.1	22	76	sugarcane
38	62	32	7	18	54	fenugreek
90	42	18	7	25	63	corn
8	33	30	5.4	36	48	mango
39	40	32	6.1	39	74	jackfruit
21	63	70	7.2	26	59	chana
30	16	9	7.3	28	47	custardapple
36	35	34	5.6	29	87	coconut

C. Soil Fertility-Infertility Prediction Module

6.1. Methodology

A total of 17 distinct characteristics of soil are represented across the data samples that are included in the soil dataset. These various characteristics include the pH value, as well as N, P, K, OC, OM, Zn, Fe, Cu, Mn, sand, silt, clay, $CaCO_3$, and CEC. Samples of the soil are taken from a diverse range of locations. Therefore, the third component of the system that is being studied will provide assistance to farmers in determining whether or not the soil is fertile. Preprocessing is then applied once the dataset has been collected, with the goals of checking for missing values and cleaning the data. Next, the X and Y variables are given their respective definitions. After that, the dataset is divided into train data and test data, on which the models are trained and evaluated, respectively. The final product is presented after first developing a web app

through which the user will enter the soil characteristics and then mapping both the data obtained from the user as well as the data samples. This step is followed by the performance of the product. The process of locating an input can be accomplished by the application of one of five distinct machine learning methods. The output is what is handed back to the user by the dataset as a consequence of the mapping. The results that were obtained are shown to the user, who may be a farmer, by way of a graphical user interface that is hosted on the web.

6.2. Algorithms

6.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm or model which can be used for classification and as well as for regression challenges. However, we mainly use it in classification challenges. SVM is generally represented as training data points in space which is divided into groups by an intelligible gap which is as far as possible. SVMs can accurately carry out a non-linear classification using a technique called the kernel trick, which is indirectly mapping the inputs into high-dimensional feature spaces.

6.2.2. Decision Tree

The Decision Tree algorithm belongs to the category of supervised learning algorithms, and we utilize it, along with other algorithms in that category, to solve a variety of regression and classification problems. The primary goal of a Decision Tree is to create a training prototype that can be used to predict the class or value of target variables by learning decision rules derived from past data (training data).

6.2.3. Bagging algorithm

Bagging classifier is an ensemble meta-estimator that fits base classifiers to random subsets of the original dataset and then aggregate their individual predictions (either by voting or average) to generate a final prediction. By integrating randomness into the construction technique of a black-box estimator (e.g., a decision tree), such a meta-estimator may often be used to lower the variance.

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Random Forest is a classifier that combines a number of decision trees on different subsets of a dataset and averages the results to increase the dataset's predicted accuracy. Instead of relying on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority votes of predictions. The greater the number of trees in the forest, the more accurate it is and the problem of overfitting is avoided.

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6.3. Dataset

The dataset is used to test and train a machine learning-based prediction model that was built using the dataset. Attributes include: State Name, District Name, Crop Year, Season, Temperature in Celsius, Soil Moisture, Area, Production, Crop and Humidity. The data is sourced from the Kaggle website. The dataset consists of 50,000 unique occurrences. Following figure lists the various attributes of soil.

Attribute	Description
pH	Soil pH Value
EC	Electric Conductivity
OC	Organic Carbon
OM	Organic Matter
N	Nitrogen Content
P	Phosphorous Content
K	Potassium Content
Zn	Zinc Content
Fe	Iron Content
Cu	Copper Content
Mn	Manganese Content
Sand	Soil Composition
Slit	
Clay	
CaCO3	Sodium Bi-Carbonate Content
CEC	Cation Exchange Capacity

Fig. 9. Soil Attributes

D. Crop Yield Prediction Module

6.1. Methodology

The data samples in the crop yield prediction system dataset represent a total of ten unique qualities. State Name, District Name, Crop Year, Season, Temperature, Humidity, Soil Moisture, Area, Production and Crop are the many variables that can be used to identify a particular crop. In order to get the most accurate results, we collect samples from all around the world. As a result, the fourth component of the system being tested will aid farmers in estimating crop yields. Once the dataset has been acquired, preprocessing is used to identify any missing values and clean up the information. In the following section, the definitions of X and Y are presented. To train and evaluate models, the dataset is separated into training and testing data sets. Mapped data from both user and sample data are presented in the final result after constructing a web app through which a user can add their various attributes. The product's performance is the next phase. It is possible to locate an input using one of five different machine learning techniques. The dataset's output is what it returns to the user after the mapping. A web-based graphical user interface displays the findings to the end user, in this case a farmer.

6.2. Algorithms

6.2.1 SVM

Support Vector Machine (SVM) is a supervised machine learning algorithm or model which can be used for classification and as well as for regression challenges. However, we mainly use it in classification challenges. SVM is generally represented as training data points in space which is divided into groups by an intelligible gap which is as far as possible. SVMs can accurately carry out a non-linear classification using a technique called the kernel trick, which is indirectly mapping the inputs into high-dimensional feature spaces.

6.2.2. Decision Tree

The Decision Tree algorithm belongs to the category of supervised learning algorithms, and we utilize it, along with other algorithms in that category, to solve a variety of regression and classification problems. The primary goal of a Decision Tree is to create a training prototype that can be used to predict the class or value of target variables by learning decision rules derived from past data (training data).

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Bagging classifier is an ensemble meta-estimator that fits base classifiers to random subsets of the original dataset and then aggregate their individual predictions (either by voting or average) to generate a final prediction. By integrating randomness into the construction technique of a black-box estimator (e.g., a decision tree), such a meta-estimator may often be used to lower the variance.

6.2.4. Random Forest

Random Forest is a classifier that combines a number of decision trees on different subsets of a dataset and averages the results to increase the dataset's predicted accuracy. Instead of relying on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority votes of predictions. The greater the number of trees in the forest, the more accurate it is and the problem of overfitting is avoided.

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6.3. Dataset

The model that will predict the fertility of soil is implemented using 5 different algorithms which are then compared and the best performing algorithm is chosen. The dataset that was utilized was the Soil dataset, which includes 17 attributes based on which fertility is predicted. The dataset was acquired from a website which consists of 100 instances.

CHAPTER 7
WEB APPLICATION

CHAPTER 7
WEB APPLICATION

7. Web Application

We developed a web application to make the modules accessible to farmers from a single site. We used PHP, Python, SQL, HTML, CSS, Bootstrap, and a few services such as Xampp for local server and PHP-admin for data storage in the creation of the complete application.

Our app's user interface is incredibly intuitive, and users will not require any additional training to operate it. We have a sign-up feature where users must create an account. To do so, they need to provide some basic information such as their name, username, email address, and password. Afterwards, they may use their username and password to login to our web application and access other features. We employ data encryption to keep the users' information safe. We have a unique username/email-id feature that prevents account duplication. We have also introduced a weather feature, allowing the users to see what kind of weather to expect in a given place by simply entering its location.

The modules that constitute our application are depicted as follows:

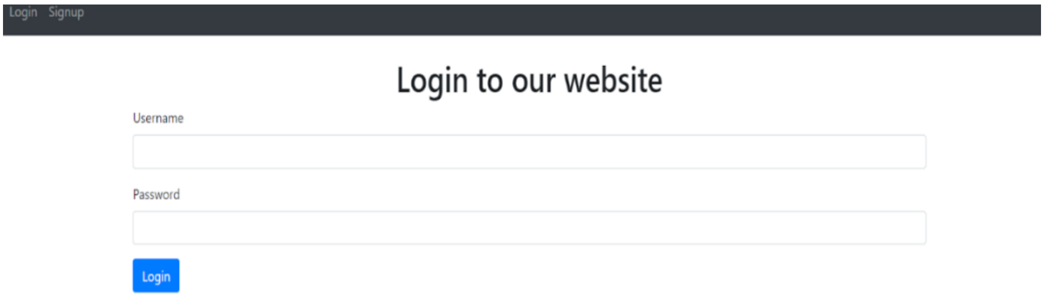

Fig 10. Login Page of Web App

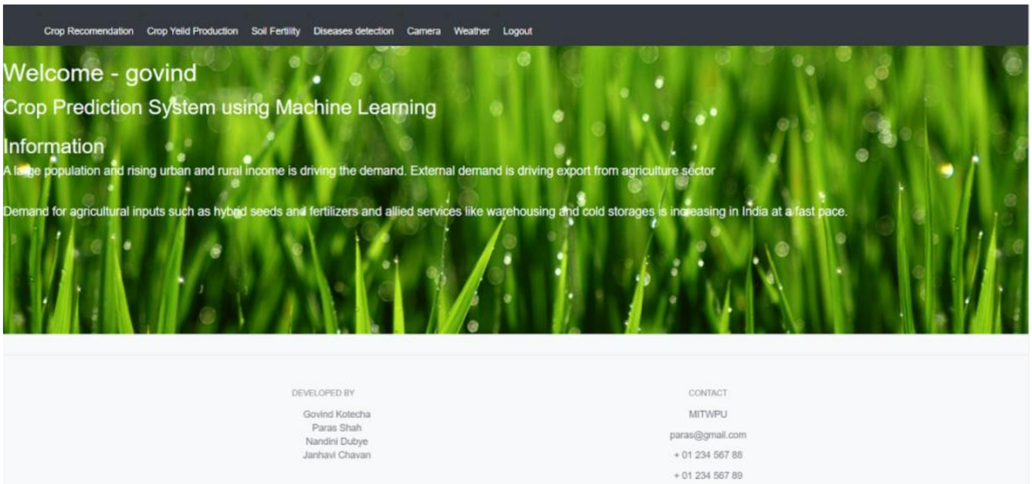

Fig 11. Web UI of App

- Disease Detection Module

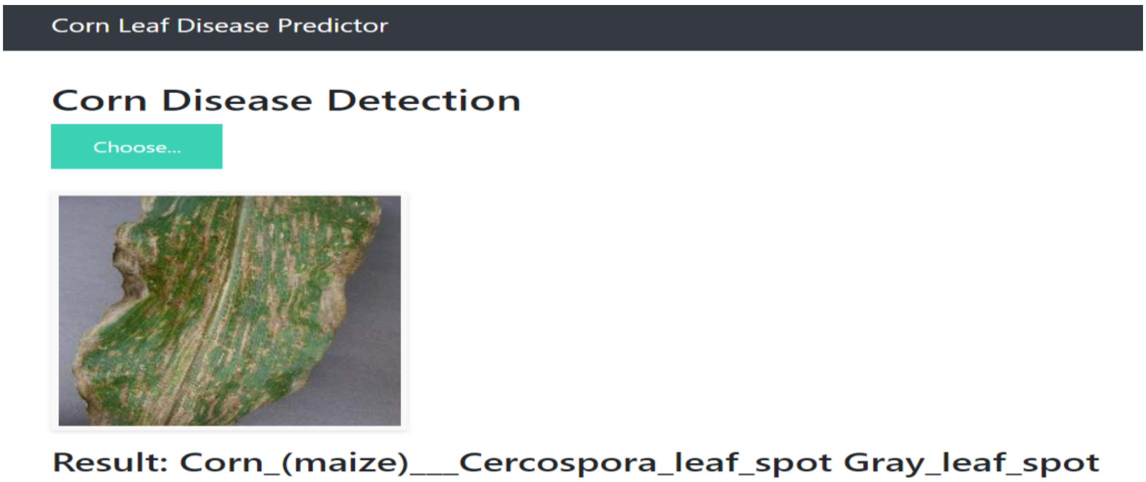

Fig 12. Disease Detection Module

- Soil Fertility-Infertility Module

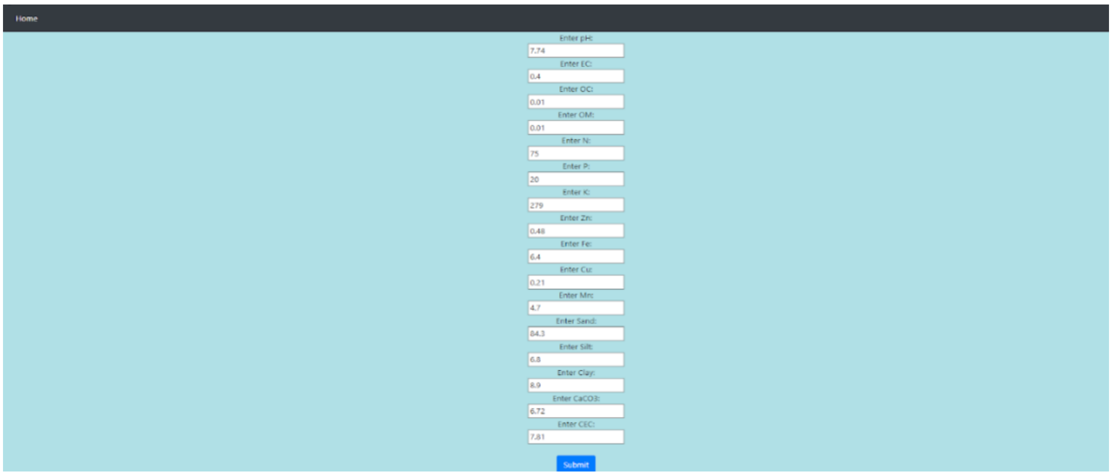

Fig 13. Soil Fertility Prediction Module

- Crop Recommendation Module

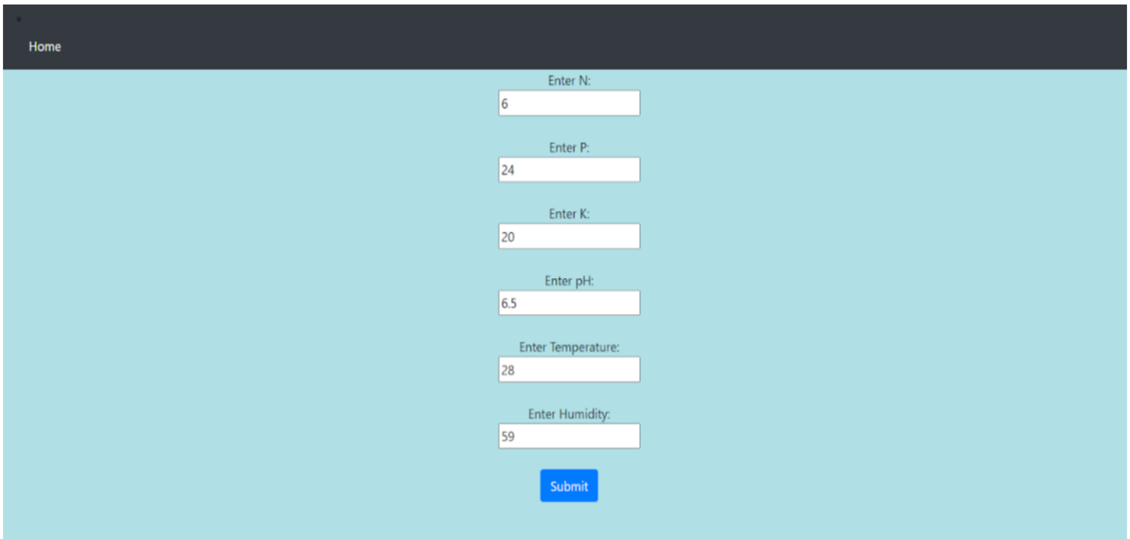

Fig 14.Crop Recommendation Module

- Crop Yield Prediction Module

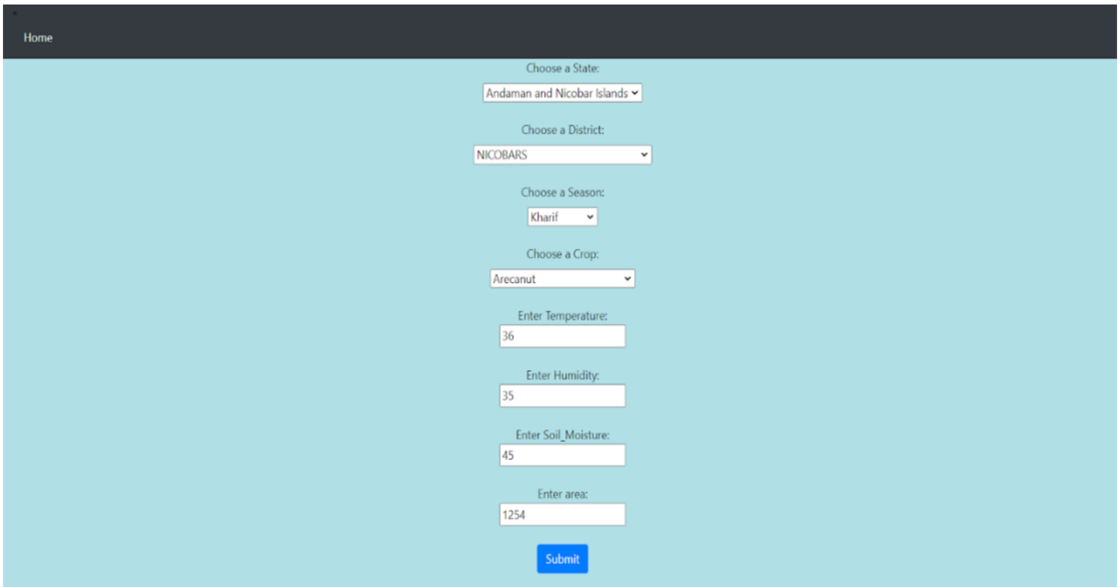

Fig:15 Crop Yield Prediction Module

CHAPTER 8
RISK MANAGEMENT AND TESTING

CHAPTER 8

RISK MANAGEMENT AND TESTING

8.1 Risk Management

What we call a risk is anything that could go wrong, whether external or internal, and whether it can be prevented through proactive measures. It's impossible to predict the outcome of any project. An infinite number of things can prevent one from accomplishing their goals in the course of a work project. Risk management allows you to control your project's schedule, budget, and quality requirements while minimizing the threats that could cause it to fail.

8.2 Testing

If a software system does not meet the requirements specified in the requirements specification or does not perform as expected, a test case is needed. There are many reasons for creating a test case, but they all revolve around ensuring that a product or service meets all applicable standards, guidelines, or customer requirements. The act of drafting a test scenario can reveal flaws in a system that would otherwise go undetected.
There are different types of test cases among which we have written functionality test cases.
Functionality tests: If an application's interface works well with the entire system and its users, this type of black box experimentation can reveal if those functions are successful or not. It is possible to conduct functional tests without accessing the software's internal structures by using system requirements or user stories as test cases. The QA team is usually responsible for writing this test case.

Table 2. Test Cases

Test Case #	Test Case Description	Test Data	Expected Result	Actual Result	Pass/Fail
1	Check response for valid email id and password for web app	Email:abc@gmail.com Password:abc@12	Login Successful	Login Successful	Pass
2	Upload the image for Disease Prediction and check if it	Corn image of Healthy Leaf	Predicts the Output as Healthy Leaf	Output predicted as Healthy Leaf	Pass

	predicts correctly.				
3	Enter the data for soil Fertility Prediction and check if it predicts correctly.	pH:7.74 ,EC:0.4, OC:0.01, OM:0.01,N:75,P:20,K:279, Zn:0.48,Fe:6.4,Cu:0.21, Mn:4.7,Sand:84.3,Silt:6.8, Clay:8.9,CaCO3:6.72,CEC7.81, Output:Fertile	Predicts soil is fertile	Output predicted as fertile	Pass
4	Enter data for Crop Recommendation and check the output.	N:26,P:24,K:38,temperature:20,Humidity:87,Ph:5.60	Chikoo Predicted	Output predicted as Chikoo	Pass

CHAPTER 9
RESULTS

CHAPTER 9
RESULTS

A. Disease Detection Module

For the purpose of classifying new categories of objects, the Deep Learning algorithms have been utilized in this research. The input that was given to the CNN model and the ResNet 50 model during the initial phase of the method was enhanced photos. The models are trained to classify objects into four categories using the image data set, which includes 7316 training photos and 1829 validation images. The models are trained using the image data set. The number of epochs that have been assigned is 25, and the batch size that has been assigned for classification is 32. We have tried assigning different epochs that are less than 25 and greater than the same, but the dataset is just the right size for a generalized model to be created at epoch 25. The overfitting and underfitting is reduced. When employing CNN and the Resnet network, the overall accuracy of classification is 96.0%, earning 70.0% for 7316 photos. The difference between the training loss and the validation loss is depicted in figure.

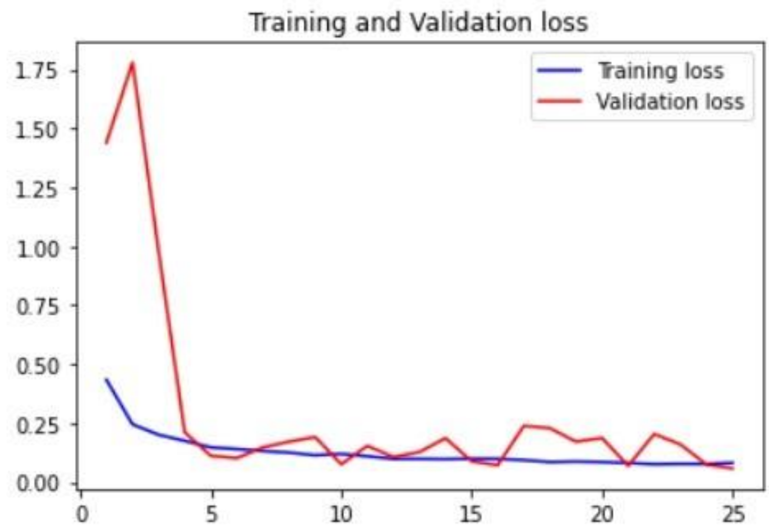

Fig. 16. Training and Validation Loss for Disease Detection Module

This figure illustrates the disparity between the accuracy of the training and validation.

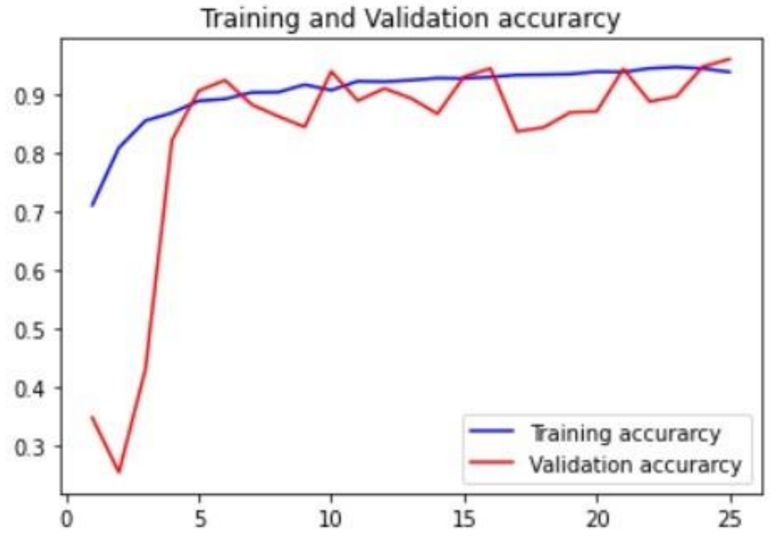

Fig. 17. Training and Validation Accuracy for Disease Detection Module

B. Soil Fertility-Infertility Module

In order to function properly, the suggested system's module for assessing soil fertility requires classification algorithms. In order to execute ML, this module use an algorithm known as the Support vector machine. Based on research that was conducted within various algorithms, it was determined that Random Forest provided incredible accuracy and performance comparable to that provided by other algorithms such as Decision tree, random forest, Bagging, XGBoost, and so on. Therefore, the Random Forest algorithm is used within the suggested system in order to search for crop recommendations that are suitable. This module of the proposed system makes use of the Random Forest algorithm in addition to some additional parameters such as pH, EC, OC, OM, N, P, K, Zn, Fe, Cu, Mn, Sand, Silt, Clay, CaCO3, and CEC. These are the primary and essential parameters that will assist in the prediction of fertility with a higher level of accuracy and efficiency in comparison to the system that is currently in use. Fig.4 is a performance measurement chart that compares a number of different algorithms. The Support vector machine came out on top, achieving an accuracy of 95.00 percent, followed by the Decision tree, random forest, Bagging, and XGBoost.

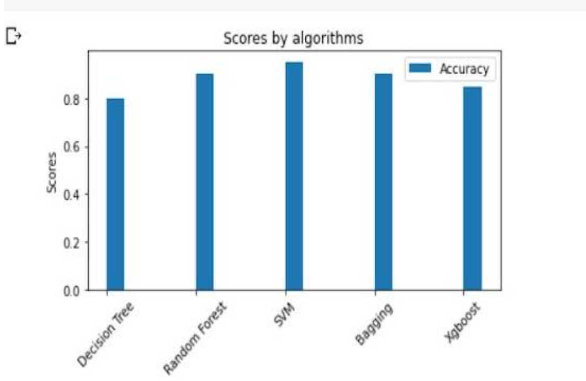

Fig. 18. Comparison of accuracies of algorithms for Soil Fertility-Infertility Module

C. Crop Recommendation Module

In order to carry out dataset mapping, the Crop Recommendation module that is a part of the proposed system requires Classification methods. The Bagging algorithm is utilized here in this module in order to carry out ML. Bagging was found, based on research carried out within various algorithms, to provide incredible accuracy and effectiveness comparable to those of other algorithms such as Decision tree, Random Forest, Support Vector Machine and XGBoost, etc. As a result, the Bagging is implemented as part of the suggested system in order to look for crop choices that are suitable. This module of the proposed system uses the Bagging algorithm in addition to some additional parameters such as phosphorus, nitrogen, potassium, pH, temperature, and humidity. These are the primary and essential nutrients of the soil, and they will help in recommending the crop that is more accurate and consistent with the soil with a higher level of accuracy and efficiency in comparison to the system that is currently in use. Below given figures are a performance measurement graph and ROC curve that compares several different algorithms. The bagging algorithm came out on top, achieving an accuracy of 96.56 percent, followed by the Decision Tree, Random Forest, SVM, and XGBOOST algorithms.

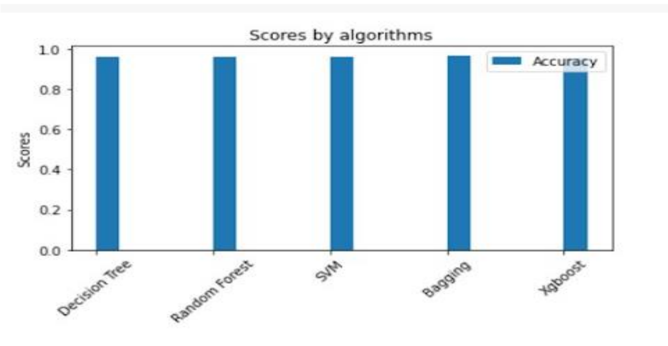

Fig. 19. Comparison of accuracies of algorithms for Crop Recommendation Module

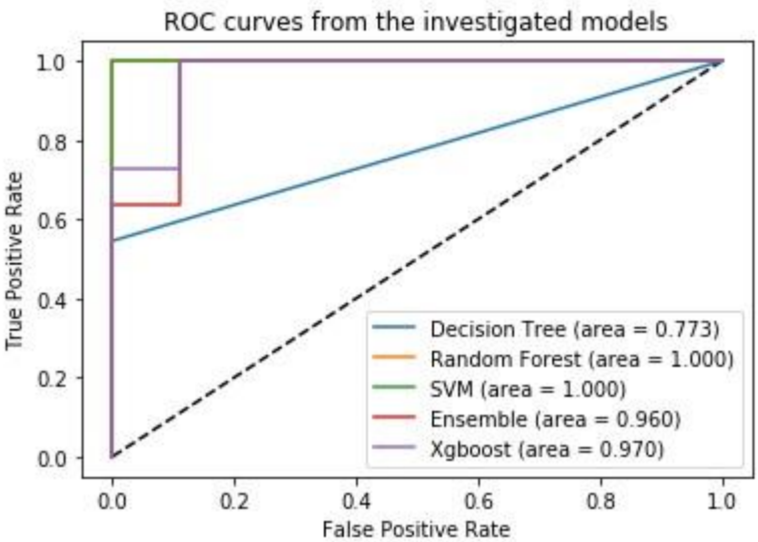

Fig. 20. ROC curves of algorithms

D. Crop Yield Prediction Module

In order to function properly, the crop yield prediction component of the system under consideration requires Classification algorithms. In order to accomplish machine learning, this module makes use of an algorithm called Gradient Boosting. According to the findings of research that was conducted within various algorithms, it was discovered that Gradient Boosting provides outrageous efficiency and precision comparable to that of other algorithms such as Decision tree Regressor, Random Forest Regressor, and Linear Regression, amongst others. As a result, the suggested system makes use of the gradient boosting algorithm in order to search for crop recommendations that are acceptable. This component of the proposed system makes use of the Boosting algorithm, in addition to some additional parameters such as State Name, District Name, Crop Year, Season, Crop, Area, and Production. These are the primary and essential parameters that will assist in predicting the yield with a higher level of accuracy and efficiency when compared to the system that is currently in place. The performance measure of a variety of methods is depicted in Figure of these algorithms, Gradient Boosting has attained the highest accuracy of 99.999 percent, followed by Random Forest regressor, Decision Tree Regressor, and Linear Regression respectively.

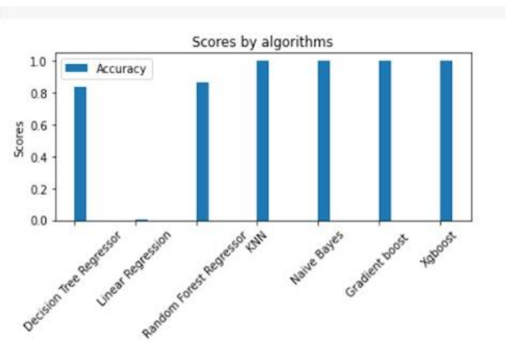

Fig. 21. Comparison of accuracies of algorithms for Crop Yield Prediction Module

CHAPTER 10
CONCLUSION

CHAPTER 10
CONCLUSION

This project presents an automated and easy to use end-to-end solution to some of the most difficult challenges faced by farmers in the agricultural domain: precise, immediate, and early diagnosis of crop diseases, crop recommendation based on different factors such as pH, nitrogen, phosphorus, potassium, temperature, relative humidity, crop yield prediction depending on multiple parameters, and determining soil fertility. By analyzing large amounts of data and interpreting the results, machine learning and deep learning frameworks provide a comprehensive picture of the process. CNN had the highest accuracy of 96.00% in detecting crop diseases. Gradient Boosting outperformed other methods in agricultural yield prediction, with an accuracy of 99.99%. In the crop recommendation system, Bagging achieved a maximum accuracy of 96.56%. Support Vector Machine recorded the maximum accuracy of 95.00% in soil fertility-infertility module.

CHAPTER 11

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REFERENCES

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CHAPTER 12
APPENDICES

A.Base Paper(S)

1. Leaf Disease Detection and Recommendation of pesticides using Convolution Neural Networks.

Leaf Disease Detection and Recommendation of Pesticides using Convolution Neural Network

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***Abstract*—Crop production problems are common in India which severely effect rural farmers, agriculture sector and the country's economy as a whole. In Crops leaf plays an important role as it gives information about the quantity and quality of agriculture yield in advance depending upon the condition of leaf. In this paper we proposed the system which works on preprocessing, feature extraction of leaf images from plant village dataset followed by convolution neural network for classification of disease and recommending Pesticides using Tensor flow technology. The main two processes that we use in our system is android application with Java Web Services and Deep Learning. We have use Convolution Neural Network with different layers five, four & three to train our model and android application as a user interface with JWS for interaction between these systems. Our results show that the highest accuracy achieved for 5-layer model with 95.05% for 15 epochs and highest validation accuracy achieved is for 5-layer model with 89.67% for 20 epochs using tensor flow.**

Keywords—CNN, Tensor flow, Leaf Disease, ANN.

I. Introduction

Technology helps human beings in increasing the production of food. However the production of food can be affected by number of factor such as climatic change, diseases, soil fertility etc. Out of these, disease plays major role to affect the production of food. Agriculture plays an important role in Indian economy. Leaf spot diseases weaken trees and shrubs by interrupting photosynthesis, the process by which plants create energy that sustains growth and defense systems and influences survival[1].Over 58% smallholder farmer depends on agriculture as their principal means of livelihood. In the developing world, more than 80 percent of the agricultural production is generated by smallholder farmers, and reports of yield loss of more than 50% due to pests and diseases are common[2].The production is decreasing day by day with various factors and one of them is diseases on plants which are not detected early stage. There is various work is done in previous years. Bacterial disease reduces plants growth very fastly so to detect this type of diseases ,Dheeb Al Bashish, Malik Braik, and Sulieman Bani-Ahmad [3] created system which detect the type of disease the plants have using image processing and color space transformation which creates device independent transformation. Identifying the disease at an early stage and suggesting the solution so that maximum harm can be avoided to increase the crop yield [4] have used ANN and K-means to classify the disease and grade the disease for. There is a need to design the automatic system to detect the leaf disease and recommend the proper pesticide. Pesticides on rice for controlling the disease damages the rice filed [5] created which will detect diseases at early stage. Which pesticides to use for which type of disease is the important task [6] gives the solution to which type of pesticides use. The paper is organized into following sections. Section 1 gives the introductory part and importance of automatic system design for early detection of leaf disease. Section 2 gives the current work done in this area. Third section include proposed methodology for leaf disease and recommending pesticide using CNN and Tensor flow tech. section 4 discuss the performance analysis and finally section 5th conclude the paper.

II. Litrarture Survey

The system by Xingchun Chen and Ron Roeber [7] focuses on Plant diseases like fungal diseases which reduces crop production. The wetness in leaf, environmental and soil data gathered from different sources. The site is connected to High plain regional climate center (HPRCC) weather server .The system is built in a zope web server with MYSQL relational databases support. Zope is as an open source web application server, is written in Python and built for content management systems. A model build by J. Duthie [8] and S. Pennypacker Et al. [9] is one of the most famous models for predicting infectiousness of disease. Both papers use a Weibull probability density function(PDF)and consider the effects of temperature and wetness duration. The proposed work is about automatic detection of diseases and diseased part present in the leaf images of plants of grape using SVM. This study contains a unique work that is it will calculate the % of infected area of plants[10]. Demonstration of the technical feasibility of a deep learning approach to enable automatic disease diagnosis through image recognition Classify Crop species & disease status of 38 different classes containing 14 crop species and 26 diseases achieving accuracy of over 99% using Deep Convolution Neural network AlexNet, GoogLeNet, Stochastic Gradian Descent[11]. The study compared the performance of PLSR, v-SVR, and GPR with the PRI and NBNDVI. The experiment was conducted in the greenhouse under controlled conditions to study the different disease symptoms effects on reflectance of the leaves for Wheat leaf rust disease [12]. CNN based on the AlexNet architecture is able to significantly outperform the baseline MLP, showing comparable performance to that of a group experts and outperforming any single expert. They have used Dataset of 2539 images of Apple Tree Species: Maxigala, Fuji Suprema and Pink Lady for Diseases: nutritional imbalances leaves with potassium and magnesium deficiency, damage (apple tree scab and Glomerella's stains),(391,558),herbicide damage (glyphosate) 325,569 healthy leaves)[13]. Robotic

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2. Detection & Prediction of Pest/Diseases using Deep Learning

DETECTION & PREDICTION OF PESTS/DISEASES USING DEEP LEARNING

1.INTRODUCTION

Deep Learning technology can accurately detect presence of pests and disease in the farms. Upon this Machine learning algorithm **CART** can even predict accurately the chance of any disease and pest attacks in future. A normal human monitoring cannot accurately predict the amount and intense of pests and disease attacked in farm for spraying correct and enough fertilizers/pesticides to eliminate the host. Therefore, and artificial **Percepton** tells the accurate value and give corrective measure of amount of pesticides/fertilizers to be sprayed at specified target areas. The aim of the project is to help the farmers to protect his farm from any kind of pests and disease attacks and eliminate them without disturbing the decorum of the soil and untouched parts of other plants. Mostly in India farmers use manual monitoring and some apps which have huge database limitations and are only bound to detection part. Since, **Prevention is better than cure**, our project aims at predicting attack of pests/diseases in future thereby making farmer to prevent such attacks.

Technology is playing a crucial in developing farms and agro-based industries. Today, it is possible to grow crops in deserts by using technology. Technology has dived into depths in agriculture sector. Automation technology is the present most demanded tool in agriculture. Many companies have come up with latest solutions in Machine Learning, Artificial Intelligence transforming agriculture into a Digital Agriculture. Many tests have proved that deploying technology in farms, will increase crop yield and farmer's revenue thereby. This paper discusses and tests Deep Learning technology implementation in agriculture.

Diagnosis is always a concern for farmers in India. At the same time due to fear of attack of pests/diseases, farmer uniformly sprays pesticides/fertilizers in whole farm which may lead to damage of soil as well as plant. The aim of this project is to make the farmer to spray a limited and enough pesticide/fertilizer at a specified target area where either pest/disease is present or maybe an occurrence of attack in future. This helps the farmers mainly to prevent any such attacks on his farm as well as eliminate them if present any by spraying in limited amount and not polluting soil and other parts of plants. Major advantage of this is to increase farmer's annual monetary revenue and minimising crop loss caused by pests/disease attacks.

1

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