AgriSense: Intelligent Plant Disease Detection System for Enhanced Agricultural Productivity

A Project Report

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SIKSHA 'O' ANUSANDHAN (DEEMED TO BE) UNIVERSITY

Bhubaneswar, Odisha, India

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CERTIFICATE

This is to certify that the project report titled "AgriSense: Intelligent Plant Disease Detection System for Enhanced Agricultural Productivity" being submitted by Vishal Kumar, Preetish Kumar Sethi, Rishu Kumar, Rishi Kant of Computer Science Engineering Branch Section-R, to the Institute of Technical Education and Research, Siksha 'O' Anusandhan (Deemed to be) University, Bhubaneswar for the partial fulfillment for the degree of Bachelor of Technology in Computer Science and Engineering is a record of original confide work carried out by them under my/our supervision and guidance. The project work, in my/our opinion, has reached the requisite standard fulfilling the requirements for the degree of Bachelor of Technology.

The results contained in this project work have not been submitted in part or full to any other University or Institute for the award of any degree or diploma.

(Dr. Binayak Panda)
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Place: Bhubaneswar, Odisha **Signature of Students**

Date: 18.06.2024

DECLARATION

We declare that this written submission represents our ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the University and can also evoke penal action from the sources which have not been properly cited or from whom proper permission has not been taken when needed.

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REPORT APPROVAL

This project report titled **“**AgriSense: Intelligent Plant Disease Detection System for Enhanced Agricultural Productivity**”** submitted by Vishal Kumar, Preetish Kumar Sethi, Rishu Kumar, Rishi Kant is approved for the degree of *Bachelor of Technology in Computer Science and Engineering*.

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PREFACE

The project focuses on using computer vision and machine learning to develop a new system called "AgriSense" to diagnose plant diseases. The system would be designed to increase agricultural productivity and vegetable safety in paddy by solving the problems faced by farmers in the accurate and timely detection of plant diseases. The first problem AgriSense aims to solve is the difficulty farmers face due to incorrect and late disease identification. Early disease detection is important to implement appropriate management and prevent crop damage. However, traditional disease detection methods, such as observation by experts, are often expensive, time-consuming, and subjective. AgriSense will offer many features to overcome these challenges. It will use image processing technology to analyze images of plant leaves taken with a smartphone or a digital camera. Deep learning algorithms, including convolutional neural networks (CNNs), will be deployed to classify the images and identify diseases based on observed patterns. The system will enable farmers to detect diseases and recommend appropriate treatment or prevention before it’s too late. Additionally, AgriSense will have a user-friendly interface accessible via mobile or web, allowing farmers to easily upload images, obtain diagnostic information, and access articles and videos related to the identified disease. The benefits of AgriSense extend beyond the individual farmer to agriculture throughout our society. By detecting diseases early and accurately, the system can help reduce crop losses, improve crop quality, and reduce dependence on pesticides. It can also help advance permaculture practices by promoting early disease detection, reducing reliance on chemicals, improving crop quality and yield, facilitating knowledge sharing, and seamlessly integrating with some fundamental permaculture design principles.

INDIVIDUAL CONTRIBUTIONS

Vishal Kumar	Dataset formatting, Model training & deployment, Model integration with backend, PPT
Preetish Kumar Sethi	Web app development, PPT, Project Report, Manuscript
Rishu Kumar	Dataset deployment, PPT, Project Report, Manuscript
Rishi Kant	Web app deployment

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1. INTRODUCTION

1.1 Introduction

Agriculture is a cornerstone of human civilization, providing the food and raw materials essential for survival and economic growth. However, one of the significant challenges faced by farmers worldwide is the timely and accurate detection of plant diseases. Plant diseases can severely impact crop yields, leading to economic losses and food shortages. Traditional methods of detecting plant diseases typically involve visual inspections by experts, which are time-consuming, subjective, and often inaccurate. These methods also require a level of expertise and resources that may not be accessible to all farmers, especially those in remote or underdeveloped areas.

To address these challenges, we present AgriSense, an intelligent plant disease detection system designed to enhance agricultural productivity. AgriSense leverages advanced image recognition algorithms to identify 28 different types of plant diseases from uploaded images of plant leaves. By utilizing a comprehensive dataset known as the Plant Village modified dataset, the system is trained to recognize disease symptoms with high precision. This early detection capability enables farmers to take prompt and effective actions to manage and treat plant diseases, ultimately improving crop yields and reducing losses.

AgriSense stands out due to its unique approach and robust technological foundation. Unlike traditional methods, AgriSense does not require farmers to have specialized knowledge or access to high-end equipment. The system is accessible via a user-friendly interface that allows farmers to upload images of plant leaves using simple devices like smartphones or tablets. Once the image is uploaded, the system processes it using advanced image recognition algorithms hosted on Google Cloud Platform's Vertex AI, ensuring consistent and accurate results across various device types.

The motivations behind the development of AgriSense are clear and focused on key aspects of agricultural improvement. First, early disease detection is crucial for effective plant disease management. By identifying diseases early, farmers can apply the necessary treatments before the diseases spread extensively. Second, improving crop yields is a direct outcome of effective disease management, which is essential for food security and economic stability. Third, enhancing agricultural productivity through innovative technological solutions like AgriSense contributes to the overall well-being of farming communities and the agricultural sector.

AgriSense simplifies the process of plant disease detection by providing a reliable and efficient solution that can be used by farmers with minimal training. The deployment of the system on Google Cloud ensures high performance, scalability, and accuracy, making it a practical tool for farmers regardless of their location or the specifications of their devices. By addressing the limitations of traditional methods and leveraging modern technology, AgriSense represents a significant advancement in the field of agricultural technology.

AgriSense is an innovative plant disease detection system that combines advanced image recognition algorithms with a user-friendly interface to provide accurate and timely disease identification. This system aims to empower farmers by improving their ability to manage plant diseases effectively, leading to better crop yields and enhanced agricultural productivity. As we continue to refine and expand AgriSense, we anticipate even greater contributions to the field of agriculture, helping to secure a more sustainable and productive future for farmers worldwide.

1.2 Project Overview

The prediction of plant diseases has become a critical area of research in agriculture, aiming to identify potential risks and improve crop yields. In recent years, machine learning algorithms have emerged as powerful tools for predicting plant diseases by leveraging patterns and relationships within large agricultural datasets. This approach utilizes extensive agricultural data, including plant images and environmental factors. On this data, we are using various algorithms and methods to enhance prediction accuracy. The use of algorithms and methods in predicting plant diseases contributes to sustainability and environmental responsibility by optimizing resource utilization, promoting preventive care and timely interventions, enabling remote monitoring and precision farming, supporting data-driven decision making, and fostering collaborative research and knowledge sharing. These efforts align agricultural practices with environmental stewardship, ultimately leading to a more sustainable and responsible farming sector. By employing these machine learning algorithms and ensemble methods, agricultural professionals can harness the power of data-driven insights to predict plant diseases accurately. These approaches enable the analysis of diverse plant attributes and patterns, leading to personalized interventions, early detection, and improved crop management outcomes in the field of agriculture. By leveraging data-driven insights, agricultural organizations can make informed decisions, reduce unnecessary expenses, and improve the overall cost-effectiveness of plant disease management.

1.3 Motivation

The objective of predicting plant diseases using AgriSense is to improve agricultural outcomes and farming efficiency by accurately identifying crops at risk of diseases. The primary objective is to detect the presence or likelihood of plant diseases at an early stage. Early detection enables timely interventions, leading to better crop management, reduced crop losses, and improved agricultural productivity. The prediction system aims to classify plants based on their risk of developing diseases. This allows farmers to allocate resources and interventions more efficiently, focusing on high-risk plants that would benefit the most from preventive measures and targeted treatments. By analyzing plant data and patterns, the prediction system aims to provide personalized interventions. Tailoring treatments and care strategies to individual plants enhances the effectiveness of interventions, reduces unnecessary pesticide use, and improves overall crop health. Accurate prediction of plant diseases helps agricultural organizations optimize resource allocation. By identifying high-risk crops, farmers can allocate inspection programs, diagnostic tests, and specialized care more effectively, ensuring that resources are used efficiently and cost-effectively. The prediction system provides farmers with data-driven decision support. By analyzing a wide range of plant attributes and patterns, the system offers insights that assist in agricultural decision-making, improving the accuracy and effectiveness of treatment plans. By utilizing AgriSense, the objective is to enhance the overall efficiency of agricultural practices. This includes reducing unnecessary field visits, minimizing unnecessary pesticide applications, and improving crop management and resource utilization. By analyzing the data in the provided *table 1*, we can see that plant death and low crop yield have been persistent problems for farmers. Agrisense helps enable early intervention and mitigation of potential losses that could otherwise hinder farmers from achieving high produce. Importantly, AgriSense is easily accessible via the internet and can be used on any device, making it a highly convenient and practical tool for farmers. With AgriSense, farmers can now proactively address plant health issues and optimize their crop yields, ultimately improving their overall agricultural productivity and profitability.

Year	Plant Species	Disease Type	Number of Incidents	Comments
2020	Tomato	Early blight	1,200	High incidence due to favorable conditions for the disease.
2020	Tomato	Late blight	1,000	Significant impact on yields.
2020	Potato	Early blight	900	Consistent with previous patterns of disease occurrence.
2020	Potato	Late blight	1,100	High incidents due to weather patterns.
2020	Corn	Common rust	800	Moderate incidence, manageable with treatments.
2020	Corn	Northern leaf blight	850	Similar to common rust in impact.
2021	Tomato	Early blight	1,250	Slight increase due to changes in agricultural practices.

2021	Tomato	Early blight	1,250	Slight increase due to changes in agricultural practices.
2021	Tomato	Late blight	950	Decrease due to better management practices.
2021	Potato	Early blight	920	Steady incidence rate.
2021	Potato	Late blight	1,150	Continued high incidence due to persistent weather patterns.
2021	Corn	Common rust	820	Slight increase from previous year.
2021	Corn	Northern leaf blight	870	Consistent with previous year's incidence.
2022	Tomato	Early blight	1,300	Continued increase, requiring enhanced management strategies.
2022	Tomato	Late blight	1,000	Stabilization of incidents with improved practices.
2022	Potato	Early blight	950	Slight increase, manageable with existing methods.
2022	Potato	Late blight	1,200	High incidence, necessitating ongoing vigilance.
2022	Corn	Common rust	850	Moderate incidence, consistent with previous trends.
2022	Corn	Northern leaf blight	900	Gradual increase, highlighting the need for continued monitoring.

TABLE 1. [Displays a comprehensive breakdown of plant disease incidents by year, type of disease, and plant species from 2020 to 2022]

1.4 Uniqueness of the Work

AgriSense simplifies access to agricultural solutions by providing an expert decision-making tool for plant disease detection, eliminating the need for logistical efforts involved in lab testing or hiring a professional. By deploying its models on Google Cloud's high-performance and multi-region servers, AgriSense ensures consistent and precise results across all device types, thereby enhancing scalability, performance, and accuracy.

This cloud-based approach addresses the challenges faced by farmers, especially those with low-end IoT devices. Instead of relying on edge computing, which can produce inconsistent results due to varying device specifications, deploying the model on the cloud guarantees uniform and reliable outcomes, regardless of the hardware capabilities of the user’s device. This is crucial for small-scale farmers who may not have access to high-end technology but still require accurate disease detection to maintain crop health.

AgriSense leverages extensive agricultural data, including plant images and environmental factors, to identify patterns and trends associated with plant diseases. By utilizing this wealth of information, AgriSense can uncover hidden patterns and relationships that may not be easily identifiable through traditional analysis methods. This approach mirrors the advantages seen in healthcare, where machine learning algorithms have significantly improved the prediction and management of diseases.

The use of ensemble methods, such as combining the predictions of multiple models, enhances the accuracy and robustness of AgriSense's predictions. These methods harness the strengths of different algorithms and reduce individual biases, resulting in more reliable predictions and increased confidence in the outcomes. By enabling personalized interventions based on specific plant characteristics and environmental factors, AgriSense provides targeted recommendations that can optimize crop management and improve agricultural productivity.

AgriSense employs various analytical techniques to handle complex and high-dimensional data, ensuring accurate plant disease detection. Early detection is a critical factor in improving crop yields and reducing losses. By identifying diseases before they spread extensively, AgriSense enables timely interventions and preventive measures, which are essential for maintaining crop health and optimizing resource use.

Moreover, AgriSense's machine learning models have the ability to continuously learn and improve over time. As more data is collected and the models are updated, the accuracy and performance of the predictions are enhanced, resulting in more effective decision support for farmers. This ongoing improvement aligns with the dynamic nature of agriculture, where new disease strains and environmental conditions continually emerge.

By providing a robust, cloud-based solution for plant disease detection, AgriSense not only enhances the efficiency of agricultural practices but also supports sustainable farming by promoting precise resource utilization and reducing unnecessary pesticide use. This ultimately contributes to a more sustainable and responsible agricultural sector, ensuring food security and environmental stewardship.

1.5 Report Layout

- Chapter 1, presents an introduction to the proposed work and its motivation.
- Chapter 2, examines the detailed literature survey.
- Chapter 3, discussed the materials and methods along with Schematic Layout/Model Diagram.
- Chapter 4, discussed the results and outputs the proposed system.
- Chapter 5, the proposed project is concluded with its overall conclusion.

2. LITERATURE SURVEY

2.1 Existing System

Traditional methods for plant disease detection involve visual inspection by experts, which can be time-consuming, subjective, and often inaccurate. These methods rely on manual observation of plant symptoms, such as discoloration, lesions, or other visual cues. This approach is limited by the expertise of the observer and the time required for inspection, which can lead to delayed detection and treatment of diseases. Visual inspection is inherently limited by human error and variability, making it difficult to achieve consistent and reliable results. The dependency on expert availability and the manual nature of the process can also result in significant delays, impacting the timeliness of interventions and potentially leading to larger outbreaks of plant diseases.

Image-based detection systems offer a modern alternative, utilizing computer vision and simple machine learning algorithms to analyze images of plants and identify diseases. These systems typically involve several key steps:

1. **Image Acquisition**: Images of plants are captured using cameras, smartphones, or other devices. This step ensures that the system has a diverse set of images to analyze, covering different angles and lighting conditions.
2. **Image Processing**: The images are processed to enhance features and remove noise. Techniques such as filtering, normalization, and contrast adjustment are applied to ensure the clarity and quality of the images.
3. **Feature Extraction**: Relevant features are extracted from the images, such as color, texture, and shape. This step involves identifying specific visual patterns that are indicative of particular plant diseases.
4. **Classification**: The extracted features are used to classify the images into different disease categories. Simple machine learning models are trained to recognize patterns associated with various diseases and categorize the images accordingly.

These image-based systems have shown promising results in detecting plant diseases, offering a more consistent and objective approach compared to traditional methods. By leveraging the power of simple machine learning, these systems can process large volumes of images quickly and accurately, providing timely detection and allowing for early intervention. This technological advancement helps mitigate the limitations of human observation, ensuring that disease detection is not only faster but also more precise. The use of image-based detection systems represents a significant improvement in agricultural practices, promoting better crop health and reducing the reliance on expert inspections. As these systems continue to evolve, they hold the potential to revolutionize plant disease management, making it more efficient and scalable.

In addition to image-based systems, there are other existing methods for plant disease detection:

1. **Spectral Analysis**: This method uses sensors to detect specific wavelengths of light reflected by plants. Healthy and diseased plants reflect light differently, and spectral analysis can identify these differences. This method is effective but requires specialized equipment and expertise.
2. **Molecular Diagnostics**: Techniques such as polymerase chain reaction (PCR) are used to detect the genetic material of pathogens in plant tissues. While highly accurate, these methods are lab-based and can be costly and time-consuming, limiting their use in the field.
3. **Electronic Nose Technology**: This method involves using sensor arrays to detect volatile organic compounds (VOCs) emitted by plants. Different diseases produce distinct VOC profiles, allowing the electronic nose to identify specific diseases. This technology is still in the research phase but shows potential for non-invasive, real-time detection.

These methods, while effective in certain contexts, each come with their own set of limitations and challenges. AgriSense aims to integrate the best features of these traditional and modern approaches, utilizing cloud-based image processing and simple machine learning to provide accurate, timely, and accessible plant disease detection for farmers worldwide.

2.2 How AgriSense Improves Upon Existing Technology

Exceptional Precision: AgriSense uses advanced technology trained on a large collection of plant images, achieving high accuracy in identifying various plant diseases. This training helps the system recognize even the smallest differences between healthy and diseased plants. By using advanced image recognition, AgriSense can detect early signs of diseases that might be missed by the human eye. The high accuracy of AgriSense ensures that farmers receive reliable diagnoses, which are crucial for timely and effective action. This precision helps in preventing the spread of diseases and optimizes pesticide use, promoting healthier crops and sustainable farming practices.

Accessibility: AgriSense is designed to be easily accessible for small-scale farmers who may not have access to advanced agricultural technologies. By using simple and affordable devices, AgriSense ensures that farmers with limited resources can still benefit from top-notch disease detection capabilities. The platform features a user-friendly interface that makes it easy for farmers to upload plant images and receive instant, accurate diagnoses. This simplicity empowers farmers to take proactive measures without needing extensive technical knowledge. Additionally, AgriSense works on a variety of devices, ensuring it can be used in different agricultural environments, from remote rural areas to more developed regions, bridging the technology gap and promoting fair access to innovative farming solutions.

2.3 Problem Identification

There are challenges faced by farmers in detecting diseases correctly and timely, which leads to unhealthy yields. AgriSense addresses these challenges by providing farmers with a cutting-edge plant disease detection system that utilizes image recognition algorithms to identify 28 types of plant diseases from uploaded images.

Lack of Expertise: Farmers often lack the necessary expertise to identify plant diseases accurately, leading to delayed or incorrect diagnosis. This can result in the spread of diseases and significant crop loss.

Limited Access to Resources: Small-scale farmers, in particular, may not have access to the necessary resources, such as equipment and training, to effectively detect and manage plant diseases. This limitation hampers their ability to maintain healthy crops and achieve good yields.

Subjective Assessment: Visual inspection of crops for disease symptoms can be subjective and prone to errors. Farmers may not have the necessary training or experience to accurately identify diseases, leading to inconsistent and unreliable diagnoses.

Inadequate Adaptation to New Diseases: Farmers may not have the knowledge or resources to adapt to new diseases, which can emerge unexpectedly and spread rapidly. This can result in reduced crop yields and profitability, as farmers struggle to manage these new threats effectively.

Time-Consuming: Traditional methods of disease detection can be time-consuming, requiring farmers to inspect each plant individually. This is especially challenging for large farms, where thorough inspection is not always possible.

High Costs: Access to expert advice or laboratory testing can be expensive, putting it out of reach for many small-scale farmers. This financial barrier prevents them from getting accurate diagnoses and timely interventions.

Geographical Barriers: Farmers in remote areas may have limited access to agricultural experts or diagnostic facilities. This isolation can delay disease identification and treatment, exacerbating crop losses.

Variability in Disease Symptoms: The symptoms of plant diseases can vary widely depending on the plant species and environmental conditions. This variability makes it difficult for farmers to rely solely on visual cues for accurate identification.

AgriSense aims to overcome these challenges by providing a reliable, easy-to-use tool that enhances the ability of farmers to detect and manage plant diseases, ensuring healthier yields and improved agricultural productivity.

3. MATERIALS AND METHODS

3.1 Dataset Description

The dataset used to train the model in AgriSense comes from a special version of the Plant Village dataset. This dataset is unique because it includes images that have been pre-processed in three different formats: color, grayscale, and segmented. This means each image of a plant leaf is available in these three types, which helps in better identifying plant diseases.

There are 162,000 images in this dataset. Each image shows a plant leaf, and these leaves can either be healthy or have some kind of disease. The dataset includes leaves from 14 different types of crops.

For each type of crop, there are different classes that the images belong to. In total, there are 38 classes. Each class represents either a specific disease that can affect the plant or a healthy leaf.

This dataset is very useful for training models to recognize plant diseases because it has a wide variety of images and covers many different diseases. By using this dataset, the model in AgriSense can learn to identify whether a plant is healthy or sick and, if it is sick, what disease it might have.

Crop Species	Disease Categories/Classes
Apple	Apple Scab, Black Rot, Cedar Apple Rust, Healthy
Blueberry	Healthy
Cherry	Powdery Mildew, Healthy
Corn	Cercospora Leaf Spot, Common Rust, Northern Leaf Blight, Healthy
Grape	Black Rot, Esca, Leaf Blight, Healthy
Orange	Haunglongbing (Citrus Greening)
Peach	Bacterial Spot, Healthy
Bell Pepper	Bacterial Spot, Healthy
Potato	Early Blight, Late Blight, Healthy
Raspberry	Healthy
Soybean	Healthy
Squash	Powdery Mildew
Strawberry	Leaf Scorch, Healthy
Tomato	Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites, Target Spot, Mosaic Virus, Yellow Leaf Curl Virus, Healthy

TABLE 2.[Different types of diseases and plants supported by the Dataset]

Plant Species	Disease Type	Number of Diseased Images
Apple	Apple Scab, Black Rot, Cedar Apple Rust	6000
Blueberry	Healthy	1500
Cherry	Powdery Mildew	1200
Corn	Cercospora Leaf Spot, Common Rust, Northern Leaf Blight	5000
Grape	Black Rot, Esca (Black Measles), Leaf Blight	4000
Orange	Citrus Greening	1800
Peach	Bacterial Spot	3000
Bell Pepper	Bacterial Spot	2800
Potato	Early Blight, Late Blight	3500
Raspberry	Healthy	1300
Soybean	Healthy	1100
Squash	Powdery Mildew	900
Strawberry	Leaf Scorch	1600
Tomato	Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites, Target Spot, Mosaic Virus, Yellow Leaf Curl Virus	8000

TABLE 3. [Number of Images per plant category]

Plant Species	Number of Healthy Images
Apple	2342
Blueberry	1500
Cherry	1000
Corn	3000
Grape	1500
Orange	1800
Peach	2100
Bell Pepper	1400
Potato	1200
Raspberry	1300
Soybean	1100
Squash	900
Strawberry	1600
Tomato	1700

TABLE 4. [Number of healthy images per plant category]

Aspect	Details
Dataset Name	Modified PlantVillage Dataset
Total Images	162,000
Image Variations	Color, grayscale, and segmented
Crop Species	14 (Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, Tomato)
Classes	38 (corresponding to plant-disease or healthy leaves)

TABLE 5. [Dataset details]

3.2 Model Diagram

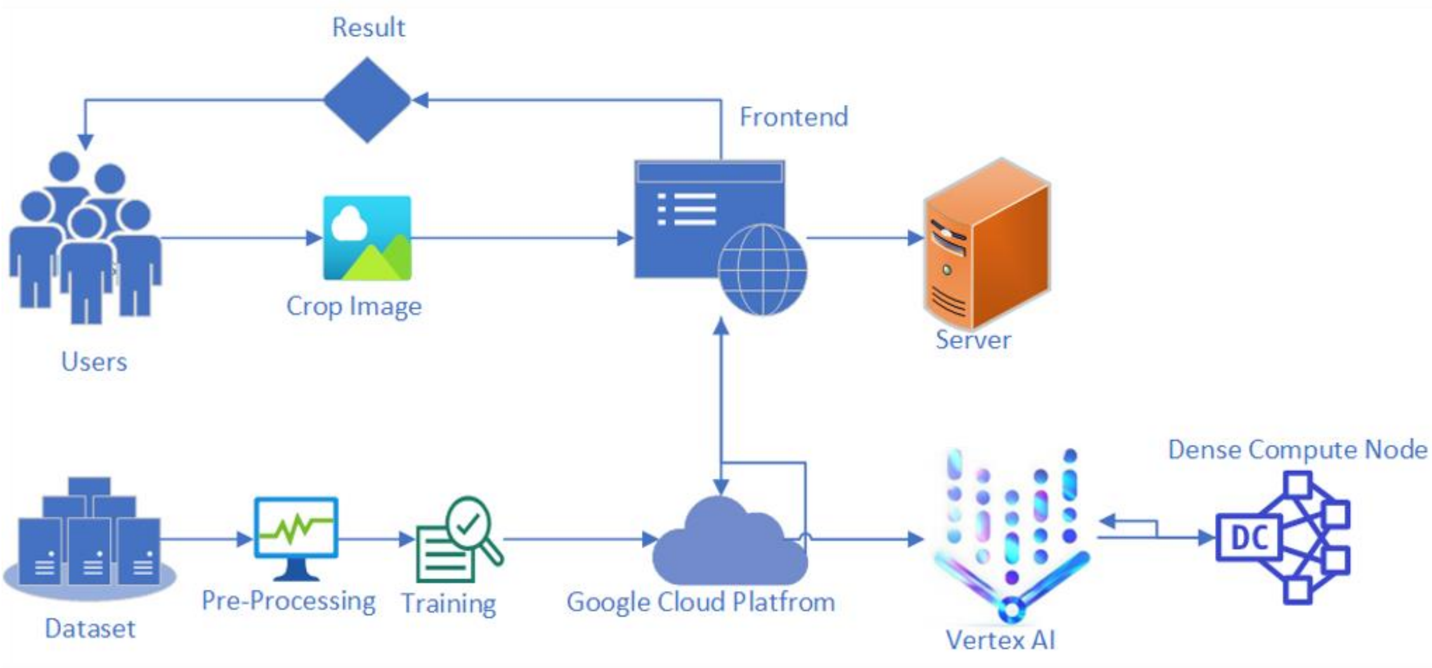

Fig. 1. *[Model diagram for disease detection on AgriSense]*

3.5 Methods Used

3.5.1 Transfer Learning:

AgriSense uses transfer learning to create a model that can accurately identify 28 types of plant diseases from images. Transfer learning involves using a model that has already been trained on a large dataset and then fine-tuning it on a smaller, specific dataset. This approach allows AgriSense to use the knowledge from the pre-trained model and apply it to plant disease detection, ensuring high accuracy even with a limited number of images.

3.5.2 Image Recognition Algorithms:

AgriSense uses image recognition algorithms to analyze and classify images of plant leaves. These algorithms can detect patterns and features that indicate the presence of diseases. By processing the uploaded images, the system can quickly and accurately identify the type of disease affecting the plant. This technology allows farmers to get reliable diagnoses without needing expert intervention.

3.5.3 Data Processing:

AgriSense processes the uploaded images using various image processing techniques. These techniques help extract relevant features and patterns necessary for identifying plant diseases. The processed data is then analyzed to determine the type of disease present. This method ensures that the system can provide precise and consistent results, helping farmers manage diseases in a timely manner.

3.5.4 User-Friendly Interface:

AgriSense features a user-friendly interface designed to be easy to navigate for farmers. The interface allows users to upload images of plant leaves and receive instant feedback on the health status of their crops. This simplicity ensures that farmers, regardless of their technical expertise, can benefit from advanced plant disease detection technology.

3.5.5 Compatibility with Low-End Devices:

AgriSense is compatible with low-end IoT devices, making it accessible to small-scale farmers. This compatibility ensures that even farmers with limited resources can use the system to detect plant diseases. By providing a solution that works on various devices, AgriSense ensures widespread adoption and utility in diverse agricultural settings.

3.5.6 Scalability and Performance:

AgriSense is deployed on high-performance cloud servers, ensuring that it can handle large volumes of data and provide consistent results. This deployment enhances the scalability and performance of the system, allowing it to serve many users simultaneously. The cloud-based model also ensures that updates and improvements can be easily implemented, keeping the system up-to-date with the latest advancements.

3.5.7 Accessibility for Small-Scale Farmers:

AgriSense is specifically designed to be accessible to small-scale farmers. The system's low cost and ease of use make it an invaluable tool for those who may not have access to advanced agricultural technologies. By empowering these farmers with reliable disease detection capabilities, AgriSense helps improve crop yields and agricultural productivity.

3.4 ToolsUsed

Google Cloud Platform:

AgriSense is built using Google Cloud Platform (GCP), a comprehensive suite of cloud computing services. GCP provides the infrastructure, tools, and services needed to develop and deploy scalable applications. By leveraging GCP, AgriSense ensures that its plant disease detection system is reliable, efficient, and capable of handling large amounts of data. GCP offers robust storage solutions, powerful computing capabilities, and advanced machine learning tools, making it an ideal platform for AgriSense.

Vertex AI:

Vertex AI is a machine learning platform on GCP that offers various tools and services for developing, training, and deploying machine learning models. AgriSense utilizes Vertex AI to train its plant disease detection model. The platform provides a range of features that streamline the process of building and managing machine learning models, including:

1. **Training:** Vertex AI allows AgriSense to train its model using large datasets of plant images. The training process involves feeding the model with images of healthy and diseased plants, allowing it to learn and recognize different disease patterns.
2. **Optimization:** Vertex AI offers tools to optimize the performance of the machine learning model. This includes tuning the model's parameters to improve accuracy and reduce errors. The platform also provides automated tools that help in finding the best configurations for the model.
3. **Scalability:** One of the key benefits of using Vertex AI is its scalability. The platform can handle large datasets and complex models, ensuring that AgriSense can process a high volume of images efficiently. This scalability is crucial for meeting the needs of farmers who rely on the system for timely and accurate disease detection.
4. **Integration:** Vertex AI seamlessly integrates with other GCP services, making it easy to manage data, deploy models, and monitor performance. This integration ensures that AgriSense can leverage the full capabilities of GCP to provide a robust and efficient service to its users.

Endpoint:

AgriSense uses an endpoint to facilitate communication between the frontend interface and the backend processing system. The endpoint serves as a bridge, receiving images from users, processing them using the trained model, and sending back the results. Here's how it works:

1. **Image Upload:** Users, typically farmers, upload images of their plant leaves through the AgriSense frontend interface. These images are sent to the endpoint for processing.
2. **Processing:** Once the images reach the endpoint, they are forwarded to the backend system where the trained model is hosted. The model analyzes the images, identifying any signs of disease. This process involves several steps, including image pre-processing, feature extraction, and disease classification.
3. **Result Delivery:** After the model processes the images and identifies any diseases, the results are sent back through the endpoint to the frontend interface. Users receive detailed information about the health status of their plants, including the type of disease detected and recommended actions.

3.5 Algorithms Used

Transfer Learning and Vertex AI for High Precision Plant Disease Detection:

Transfer learning and Vertex AI are powerful tools in the field of machine learning that can be used to create high precision models for plant disease detection. Let's explore how these techniques can be used to develop accurate models using the Plant Village dataset.

What is Transfer Learning?

Transfer learning is a machine learning technique where a pre-trained model is fine-tuned on a new dataset to adapt to a specific task. This technique is particularly useful when the new dataset is small or has limited data. Transfer learning allows the model to leverage the knowledge it has gained from the pre-trained model and adapt it to the new task, resulting in better performance.

What is Vertex AI?

Vertex AI is a fully managed, unified AI development platform that provides tools and services for building and deploying machine learning models. It is built on top of Google's AI research and infrastructure and provides a secure and responsible approach to AI development.

How to Use Transfer Learning and Vertex AI for Plant Disease Detection?

Here are the steps to use transfer learning and Vertex AI for plant disease detection:

1. **Preprocessing:** Preprocess the Plant Village dataset by resizing the images, normalizing the pixel values, and converting them to grayscale.
2. **Transfer Learning:** Use a pre-trained convolutional neural network (CNN) such as VGG16 or ResNet50 as the base model. This model has already been trained on a large dataset and has learned to recognize general features such as edges, lines, and shapes.
3. **Fine-Tuning:** Fine-tune the pre-trained model on the Plant Village dataset by adjusting the weights and biases of the model to adapt to the specific task of plant disease detection.
4. **Training:** Train the fine-tuned model on the Plant Village dataset using a suitable optimizer and loss function.
5. **Evaluation**: Evaluate the performance of the model using metrics such as accuracy, precision, and recall.
6. **Deployment:** Deploy the trained model using Vertex AI, which provides a fully managed platform for deploying and managing machine learning models.

The above processes are taken care of automatically by Google Cloud Platform as we just need to upload the preprocessed dataset to train the model. The most optimal model is automatically selected by the GCP based on the use case and a fine tuned model is trained with custom parameters to best fit the dataset, this model is then evaluated and can be deployed right in the Google Cloud Platform for the frontend to connect and be used in any application, which in our case is a Webapp.

Benefits of Using Transfer Learning and Vertex AI

Using transfer learning and Vertex AI for plant disease detection has several benefits:

1. **Improved Accuracy:** Transfer learning allows the model to leverage the knowledge it has gained from the pre-trained model and adapt it to the new task, resulting in better performance.
2. **Reduced Training Time**: Fine-tuning a pre-trained model is faster than training a model from scratch, which can save time and resources.
3. **Improved Interpretability**: Vertex AI provides tools for explainable AI, which allows us to understand how the model is making predictions and identify areas for improvement.
4. **Scalability:** Vertex AI provides a fully managed platform for deploying and managing machine learning models, which allows us to scale our models to meet the needs of our application.

Transfer learning and Vertex AI are powerful tools that can be used to create high precision models for plant disease detection. By fine-tuning a pre-trained model on the Plant Village dataset and deploying it using Vertex AI, we can develop accurate models that can be used to detect plant diseases with high precision.

3.6 Packages Used

- Streamlit
- Keras
- Numpy
- Csv
- Json

3.7 Evaluation Measures Used

Evaluation Measures

Evaluation Measures	Equation
Precision	Precision= (True Positive) / (True Positive + False Positive)
Recall	There are proportion of number of items as positive to total. Recall= (True Positive) / (True Positive + False Negative)
Average Precision	It is a metric that measures the average of precision scores at each point where a relevant item is retrieved in ranked results. $AP = \sum_{k=0}^{k=n-1} [Recalls(k) - Recalls(k+1)] * Precisions(k)$ $Recalls(n) = 0, Precisions(n) = 1$ $n = Number\ of\ thresholds.$

Table 6 [Formulas used for Evaluation]

4. RESULTS

4.1 System Specification

4.1.1 Hardware Specifications

1. **Google Cloud Platform (GCP)**

- **Compute Engine**: Virtual machines with high CPU and memory configurations to handle large-scale image processing and machine learning model training.
    - **Instance Types**: n1-standard-4 (4 vCPUs, 15 GB memory) to n1-standard-16 (16 vCPUs, 60 GB memory) depending on the workload.
    - **Storage**: SSD Persistent Disk for fast read/write operations.
    - **Networking**: High bandwidth network interface for quick data transfer.

2. **Cloud Storage**:

- **Bucket Storage**: For storing large datasets of plant images and processed data.
    - **Standard Storage**: For frequently accessed data.
    - **Nearline Storage**: For less frequently accessed data.

3. **Cloud Functions**:

- **Serverless Compute**: To run backend processes and image processing tasks on-demand without managing servers.

4.1.2 Software Specifications

1. Frontend Framework

Streamlit

- **Purpose**: Streamlit is a powerful and user-friendly framework for building interactive web applications in Python. It allows for quick prototyping and deployment of data-driven applications.
- **Features**:
    - **Ease of Use**: Simple Python scripts can be turned into interactive apps.
    - **Real-Time Updates**: Automatically updates the web interface when changes are made to the underlying code.

   - **Integration**: Easy integration with Python libraries like Pandas, NumPy, Matplotlib, and Plotly for data visualization.
   - **Deployment**: Supports cloud deployment on platforms like Google Cloud, AWS, and Streamlit Sharing.

2. Programming Language

Python

- **Purpose**: Python is the primary programming language for developing the core functionalities of AgriSense.
- **Features**:
   - **Libraries and Frameworks**: Extensive libraries for data processing (Pandas, NumPy), machine learning (scikit-learn, TensorFlow, Keras), and image processing.
   - **Community Support**: Large community and extensive documentation for troubleshooting and support.
   - **Versatility**: Can be used for backend processing, data analysis, and frontend development with frameworks like Streamlit.

4.2 Parameters Used

We modified the dataset to include grayscale and segmented images of all 28 plant types, as well as healthy images of plant types, along with high-quality colored images, to ensure the accuracy and precision of our model for plant diseases prediction.

The *table 8 and table 9* below provides a detailed breakdown of the number of images available for various crops, including apples, blueberries, cherries, and more. For each crop, it lists the total number of images, the number of grayscale images, and the number of segmented images. The total number of images column indicates how many pictures were taken for each crop.

The grayscale images column shows how many of these pictures have been converted to black and white, providing a simpler view of the crops without color information. Lastly, the segmented images column indicates how many of these pictures have been processed to highlight specific parts of the image, such as identifying particular features of the crops. For instance, apples have 1,645 total images, all of which are also available as grayscale and segmented images. This pattern is consistent across all the crops listed in the table, ensuring a comprehensive dataset for various types of image analysis.

Crop	Number of Images	Number of Grayscale Images	Number of Segmented Images
Apple	1,645	1,645	1,645
Blueberry	1,502	1,502	1,502
Cherry	854	854	854
Corn	1,162	1,162	1,162
Grape	423	423	423
Orange	5,507	5,507	5,507
Peach	360	360	360
Pepper	1,478	1,478	1,478
Potato	152	152	152
Raspberry	371	371	371
Soybean	5,090	5,090	5,090
Squash	1,835	1,835	1,835
Strawberry	456	456	456
Tomato	1,591	1,591	1,591

Table 7. [Modified Dataset containing grayscale and segmented images for healthy crops]

Crop	Number of Images	Number of Grayscale Images	Number of Segmented Images
Apple (Scab)	630	630	630
Apple (Rot)	621	621	621
Apple (Blotch)	275	275	275
Cherry (Powdery Mildew)	1,052	1,052	1,052
Corn (Blight)	513	513	513
Corn (Common Rust)	1,192	1,192	1,192
Corn (Gray Leaf Spot)	985	985	985
Grape (Black Rot)	1,180	1,180	1,180
Grape (Esca)	1,383	1,383	1,383
Grape (Leaf Blight)	1,076	1,076	1,076
Orange (Haunglongbing)	5,507	5,507	5,507
Peach (Bacterial Spot)	2,297	2,297	2,297
Pepper (Bacterial Spot)	997	997	997
Potato (Early Blight)	1,000	1,000	1,000
Squash (Powdery Mildew)	1,835	1,835	1,835
Strawberry (Leaf Scorch)	1,109	1,109	1,109
Tomato (Bacterial Spot)	2,127	2,127	2,127
Tomato (Early Blight)	1,000	1,000	1,000
Tomato (Late Blight)	1,909	1,909	1,909
Tomato (Leaf Mold)	952	952	952
Tomato (Septoria Leaf Spot)	1,771	1,771	1,771
Tomato (Spider Mites)	1,676	1,676	1,676
Tomato (Target Spot)	1,404	1,404	1,404
Tomato (Yellow Leaf Curl Virus)	5,357	5,357	5,357
Tomato (Mosaic Virus)	373	373	373

Table 8 [Modified Dataset used for diseased plants containing grayscale and segmented images]

Data Split	Number of Images	Percentage
Training Set	129,942	80%
Validation Set	16,336	10%
Test Set	16,564	10%

Table 9. [Training Validation and Testing Split]

4.3 Experimental Outcomes

Here is the step-by-step process of how to check for diseases in plants using the Agrisense platform:

Step 1: Take High-Quality Photos of the Plant Leaf

- ➢ Take high-quality photos of the plant leaf in a clear background with adequate lighting.
- ➢ Ensure the photos are well-lit and in focus to help the Agrisense platform accurately identify the plant disease like shown in the figure 14.

Fig. 2. *[Images of different leaves to demonstrate good images for upload]*

Step 2: Upload the Image to the Web Interface

- ➢ Go to the Agrisense web interface and click on the "Upload Image" button.
- ➢ Select the image you took in Step 1 and upload it to the platform.

Fig. 3. *[Image of web app layout showing where to upload the images]*

Step 3: Wait for the Frontend to Send the Image to the Vertex AI Endpoint

- ➢ Once the image is uploaded, the frontend will send it to the Vertex AI endpoint where the model is deployed and live for processing.
- ➢ Wait for the model to process the image and generate a result.

Step 4: Receive the Result

- ➢ The result will be sent back to the frontend and displayed as a percentage of confidence and the identified disease.
- ➢ The result will also include links on how to proceed with the treatment.

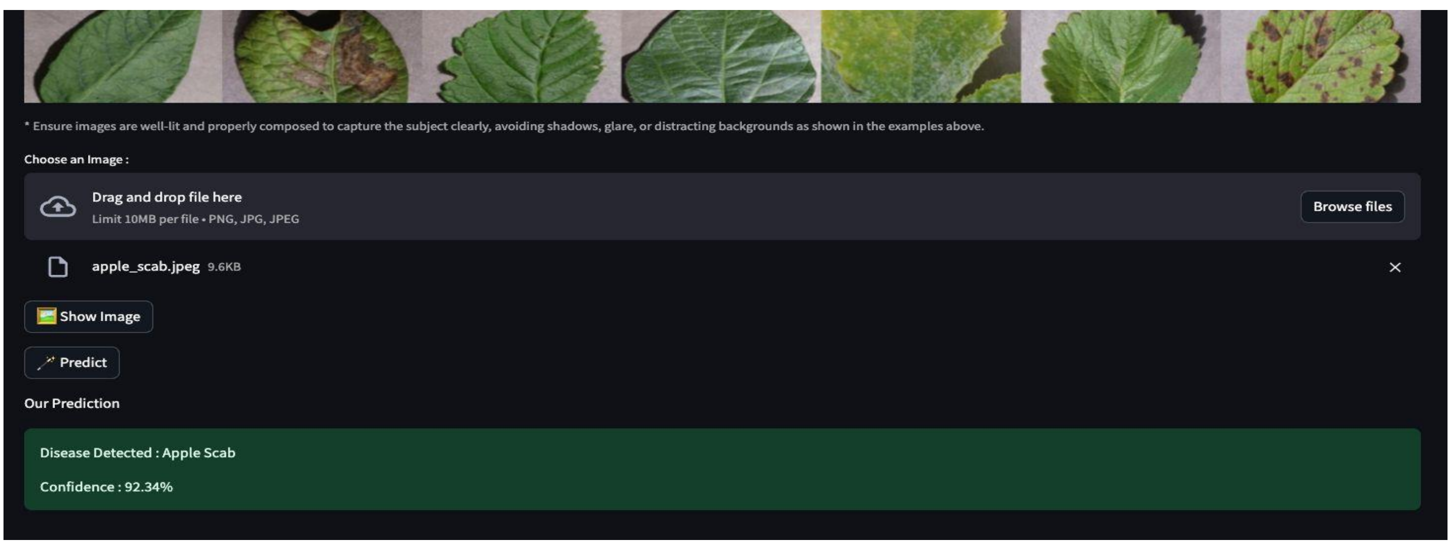

Fig. 4. *[Image of disease detected]*

To train the Model:

- ➢ The training of the model was done using a modified dataset that contains grayscale and segmented images for each type to enhance accuracy.

➢ The dataset was uploaded to a Google Cloud bucket and then given to Vertex AI.

➢ Vertex AI asked for the training, validation, and testing split, which was set to 80/10/10.

➢ The model was trained and evaluated for performance and accuracy.

Deploy the Model on Vertex AI:

➢ Once the model was trained and evaluated, it was deployed on Vertex AI as an endpoint.

➢ This allows the model to be accessed and used by the Agrisense platform to identify plant diseases.

By following these steps, you can use the Agrisense platform to check for diseases in plants and receive accurate results.

Models Accuracy Output

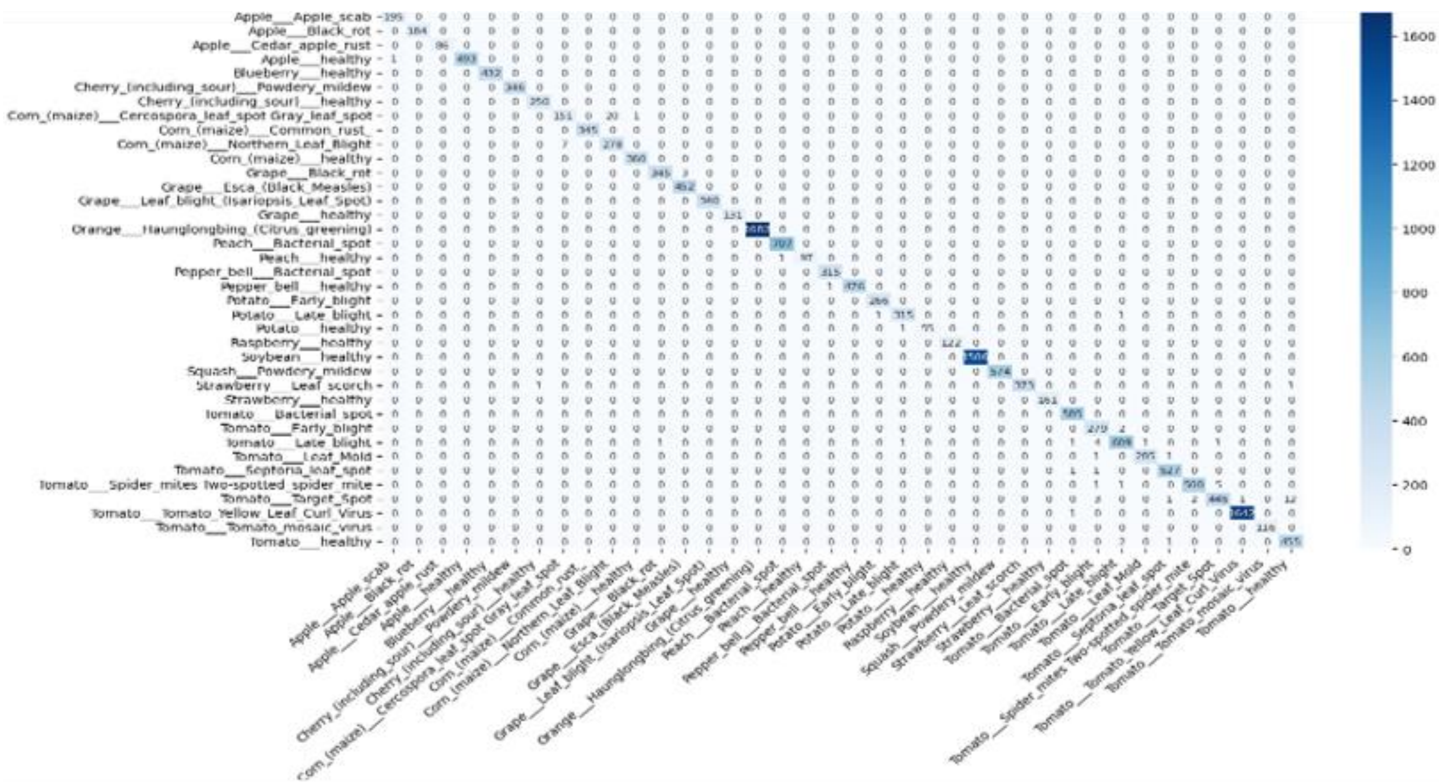

Fig. 5. *[Confusion Matrix of the model]*

Each row of the matrix represents the actual disease, and each column represents the predicted disease. The diagonal cells show the number of correct predictions for each disease. Higher numbers in these cells indicate better accuracy for that disease.

The darker the color of a cell, the higher the number it represents. This visual helps quickly see which diseases are accurately predicted and where mistakes are happening. If most of the dark cells are along the diagonal, the system is performing well overall.

FINAL DATASET DESCRIPTION

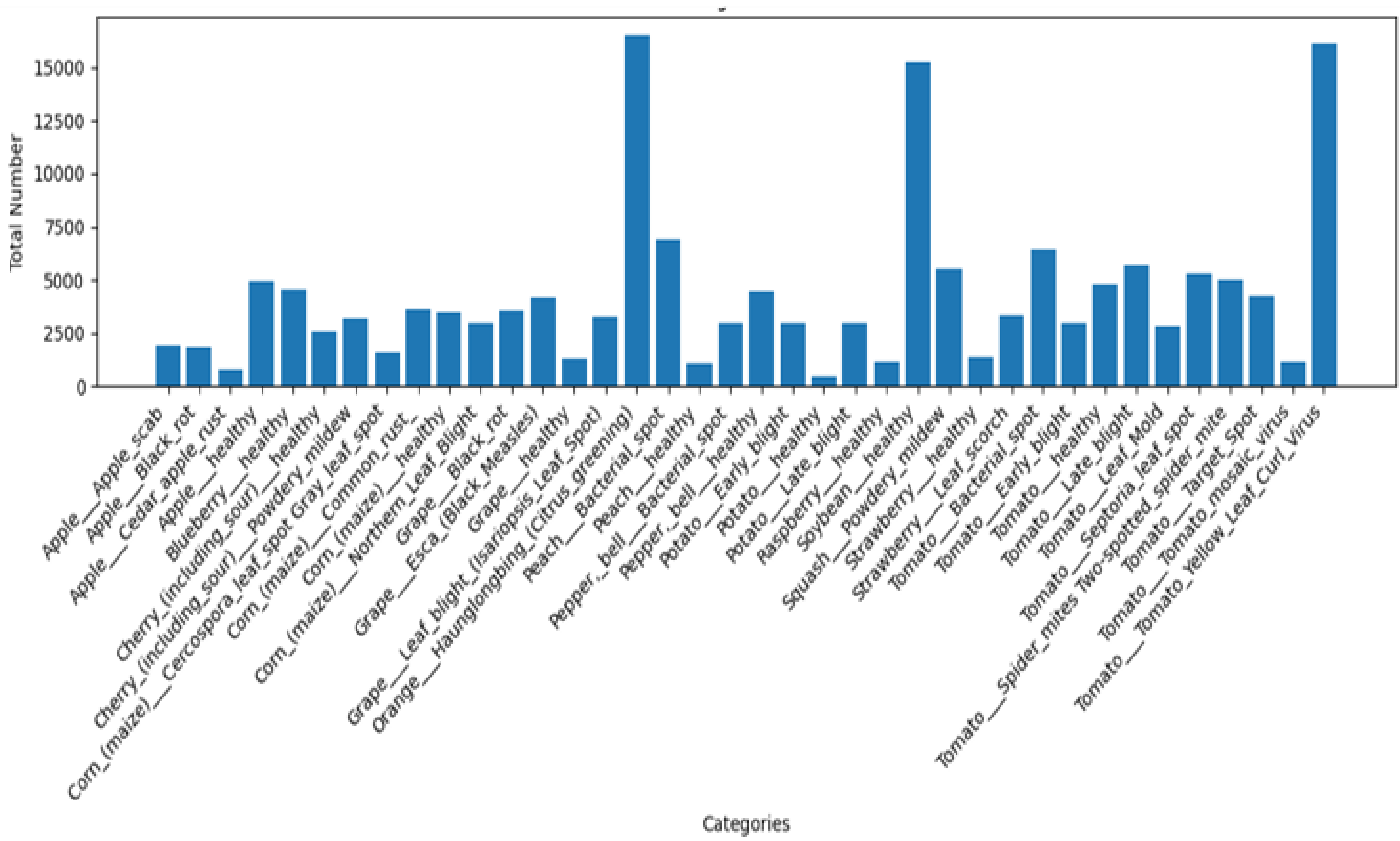

Fig. 6. *[Bar graph representing no. of images to their corresponding classes]*

- ➢ The machine learning model in AgriSense is trained on a modified Plant Village dataset, which contains a diverse range of images representing various plant diseases. Unlike other Plant Village datasets it comes with pre-processed images in color, grayscale and segmented format. Including all the variations the dataset offers 162,000 images to train our model.
- ➢ The dataset covers 14 crop species including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato. The dataset is organized into 38 classes corresponding to plant-disease or healthy leaves.

Precision-Recall Plot

The image below shows a graph with "Precision" on the y-axis and "Recall" on the x-axis, both reaching 100%. This is known as a Precision-Recall plot.

- Precision measures how many of the identified items are correct.
- Recall measures how many of the actual correct items were identified.

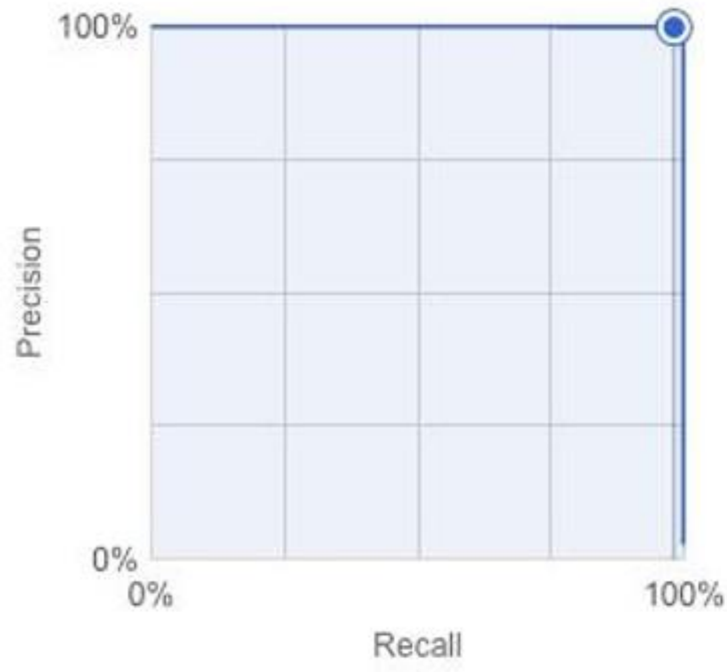

Fig. 7. [*Precision-Recall curve at 50% confidence Threshold]*

Precision and Recall vs. Confidence Threshold Plot

The second image bellow shows two lines representing "Recall" and "Precision" against a "Confidence Threshold" on the x-axis.

- Confidence Threshold is the cut-off value used to decide whether an item is identified as positive or not.
- As the threshold changes, the balance between precision and recall also changes.

The blue line (Recall) starts high and drops sharply as the threshold increases.
The red line (Precision) starts lower and then increases, but eventually drops as well. This indicates that at very high thresholds, the precision is high, meaning most identified items are correct.

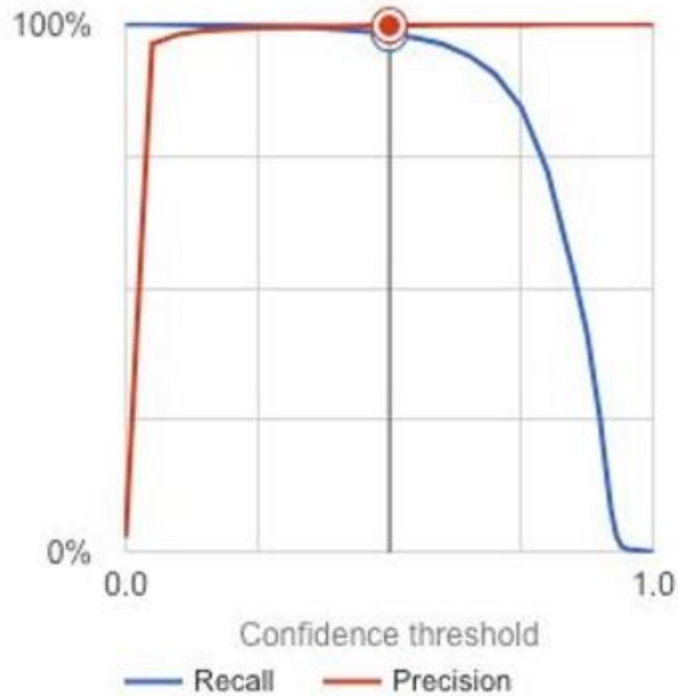

Fig. 8. [*Precision-Recall curve along full range of confidence threshold]*

Metric	Value
Average Precision	0.999
Precision	99.7%
Recall	98.1%

Table 10. [This table shows three key performance metrics for machine learning model]

1. **Average Precision:** The model's precision across all categories is extremely high, at 0.999 (almost perfect).
2. **Precision:** When the model predicts a positive result, it is correct 99.7% of the time.
3. **Recall:** The model correctly identifies 98.1% of all actual positive cases.

4.4 Results Analysis and Validation

After deploying the model using Streamlit, we evaluated its performance. Here's a straightforward summary of our analysis and validation process:

1. Accuracy and Performance Metrics

- **Confusion Matrix**: This table shows how often the model correctly identified diseases. Each row represents the actual disease, while each column shows the predicted disease. Correct predictions are along the diagonal.
- **Precision and Recall**: Precision measures how many of the identified diseases were correct. Recall measures how many actual diseases were identified correctly.

2. Model Deployment and Use

- **Frontend Deployment**: The model was deployed using Streamlit, a tool that makes it easy to create interactive web applications with Python. Streamlit updates in real-time, making the app responsive and user-friendly.
- **Cloud Integration**: The model is hosted on Google Cloud using Vertex AI. This allows the system to process images and return results quickly.

3. Validation Process

- **Step-by-Step Validation**:

    a. **Image Upload**: Users upload images of plant leaves to the Streamlit app.
    b. **Processing**: The app sends the image to Vertex AI for analysis.
    c. **Result Display**: The app shows the identified disease and the confidence level of the prediction.

4. Performance Evaluation

- **Precision-Recall Plot**: This graph shows the trade-off between precision and recall. High precision and recall indicate the model is performing well.
- **Confidence Threshold**: Adjusting this value affects precision and recall. Higher thresholds mean higher precision but lower recall, and vice versa.

5. CONCLUSIONS

The AgriSense project represents a noteworthy step forward in the field of agricultural technology, particularly in the realm of plant disease detection.

This intelligent system, which leverages computer vision and machine learning, addresses the critical need for timely and accurate identification of plant diseases, a challenge that has long plagued the agricultural sector.

Key Achievements of AgriSense

1. **Advanced Disease Detection:** AgriSense utilizes state-of-the-art image processing and deep learning techniques to analyze images of plant leaves, enabling it to accurately identify 28 different types of plant diseases. This capability is powered by transfer learning, which has been trained on a modified dataset, ensuring high precision and reliability.
2. **User-Friendly Interface:** The system is designed with accessibility in mind. Farmers can easily upload images using their smartphones or digital cameras, and receive diagnostic results through a mobile or web interface. This eliminates the need for specialized knowledge or expensive equipment, making advanced agricultural technology available to a broader audience.
3. **Scalability and Consistency:** The deployment of AgriSense on Google Cloud ensures that the system is both scalable and consistent. The model can be improved by retraining on the latest datasets, allowing it to address new and emerging plant diseases effectively and immediately.
4. **Promotion of Sustainable Practices:** AgriSense also contributes to sustainable farming practices by reducing the dependency on pesticides. By accurately identifying diseases, the system helps in applying precise treatments, thereby minimizing unnecessary chemical use and promoting environmental health.

Impact on the Agricultural Sector

AgriSense has the potential to improve agricultural practices in several ways:

- **Enhanced Productivity:** With accurate and timely disease detection, farmers can ensure healthier crops and higher yields. This directly translates to improved economic outcomes for farming communities.
- **Cost Efficiency:** By reducing the need for expert inspections and unnecessary pesticide applications, AgriSense helps in lowering operational costs for farmers. The system's accessibility ensures that even small-scale farmers can benefit from advanced agricultural technology.

- **Knowledge Sharing:** The system not only provides disease diagnostics but also offers access to articles and videos related to the identified diseases. This feature promotes knowledge sharing and helps farmers stay informed about best practices and new developments in crop management.

Future Directions

As the AgriSense system continues to evolve, several enhancements and expansions can be anticipated:

- **Increased Dataset and Disease Coverage:** Expanding the dataset to include more plant species and diseases will further improve the system's accuracy and applicability.
- **Continuous Learning and Improvement:** The machine learning models used by AgriSense have the capability to continuously learn from new data, ensuring the system remains up-to-date with the latest disease patterns and environmental changes.
- **Advanced Security Protocols:** Implementing advanced security protocols to protect sensitive agricultural data and ensure the privacy and integrity of the information processed by the system.
- **Enhanced Integration:** Enhancing integration with broader agricultural management platforms to provide comprehensive solutions for crop management, including pest control and nutrient management.

6. REFERENCES

1. Google Cloud Platform. (n.d.). Vertex AI.
2. Abdallah Ali, PlantVillage Dataset, Kaggle
3. Li, L., Zhang, S., & Wang, B. (2021). Plant disease detection and classification by deep learning—a review. IEEE Access, 9, 56683-56698.
4. Kumar, R., Chug, A., Singh, A. P., & Singh, D. (2022). A Systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a review. Journal of Sensors, 2022.
5. Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Computers and electronics in agriculture, 153, 46-53.

7. APPENDICES

1. Vertex AI: A fully managed, unified AI development platform provided by Google Cloud that offers tools and services for building and deploying machine learning models.

2. Transfer Learning: A machine learning technique where a pre-trained model is fine-tuned on a new dataset to adapt to a specific task.

3. Precision-Recall Plot: A graph that shows the trade-off between precision (how many of the identified items are correct) and recall (how many of the actual correct items were identified) for a machine learning model.

4. Confidence Threshold: The cut-off value used to decide whether an item is identified as positive or not in a machine learning model.

5. Average Precision: A performance metric that measures the model's precision across all categories.

6. Precision: The percentage of time the model is correct when it predicts a positive result.

7. Recall: The percentage of actual positive cases that the model correctly identifies.

8. Sustainable Farming: Farming practices that are environmentally responsible, economically viable, and socially equitable, ensuring long-term food production.

9. Personalized Interventions: Tailored treatments and care strategies based on individual plant characteristics and environmental factors.

10. Continuous Learning: The ability of machine learning models to continuously learn and improve from new data over time.

11. Multi-Tenancy: The ability of a system to provide isolated and secure environments for multiple users or groups.

12. Plant Village Dataset: A comprehensive dataset of over 50,000 expertly curated images of healthy and infected leaves of crop plants.

13. Grayscale Images: Images that have been converted to black and white, providing a simpler view without color information.

14. Segmented Images: Images that have been processed to highlight specific parts or features of the plant.

15. Precision-Recall Curve: A graph that shows the trade-off between precision and recall across different confidence threshold values.

8. REFLECTION OF THE TEAM MEMBERS ON THE PROJECT

Working on AgriSense, our Intelligent Plant Disease Detection System, has been an enriching experience for each of us. As a team, we have grown both professionally and personally while contributing to a project that has the potential to greatly enhance agricultural productivity.

Vishal Kumar focused on dataset formatting, model training and deployment, and integrating the model with the backend. Reflecting on his work, Vishal notes how the project challenged his understanding of machine learning and backend integration, pushing him to find new solutions to complex problems. The experience deepened his technical skills and showed him the importance of careful data preparation and model accuracy.

Preetish Kumar Sethi played a key role in web app development and contributed significantly to the PPT, project report, and manuscript. Preetish found the project to be a great chance to apply his theoretical knowledge in a practical way. Building the web application from scratch helped him improve his development skills and learn about designing for users. He valued the need for constant communication and coordination with his teammates throughout the project.

Rishu Kumar focused on creating the PPT, project report, and manuscript. Through this project, Rishu developed a deeper understanding of the importance of clear and effective communication. Writing the documentation and presentations helped him learn how to explain complex technical ideas in a simple way. He felt proud to contribute to the materials that would represent their hard work to others.

Rishi Kant was responsible for deploying the web app. This role presented Rishi with the challenge of making sure the application was not only functional but also scalable and secure. Reflecting on his contribution, Rishi appreciated the hands-on experience with deployment environments and the satisfaction of seeing the application come to life. This project highlighted the importance of deployment in making sure the application works well in real-world situations.

Overall, the AgriSense project has been a significant milestone for our team. It allowed us to apply what we've learned in our studies to solve real-world problems and develop a solution that can benefit farmers. Working together to bring AgriSense to life has strengthened our teamwork and communication skills, leaving us with a strong sense of achievement and readiness for future challenges.

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