AI-powered Precision Agriculture using Autonomous Drones and IoT Sensors

Final Year Project Proposal

Session 2021-2025

A project submitted in partial fulfilment of the requirements
for the degree
of
Bachelor of Science in Computer Science

Department of Computer Science

Namal University Mianwali

16 November 2024

Project Registration

Project ID (for office use)						
Type of project	[ ] Traditional		[✓] Industrial		[ ] Continuing	
Nature of project	[ ] **D**evelopment		[ ] **R**esearch		[✓] **R**&**D**	
Area of specialisation						
Project Group Members						
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Declaration: FYP group members have cleared all prerequisites courses (mentioned below) for FYP-I as per their degree requirements. (CS-131 Object Oriented Programming, CS-260 Software Engineering Concepts, CS-250 Database Systems, ENG-111 Technical Writing and Communication)						

Plagiarism Free Certificate

This is to certify that, I am ________________________ S/D/o _______________________, group member of FYP under registration no _____________________ at Computer Science Department, Namal University. I declare that my FYP proposal is checked by my supervisor and the similarity index is ________% that is less than 20%, an acceptable limit by HEC. Report is attached herewith as Appendix A.

Date: ____________

Name of Group Member 1: ________________________ Signature: _____________

Name of Group Member 2: ________________________ Signature: _____________

Name of Supervisor: _______________________

Signature: _______________________

Project Abstract

Traditional farming practices are increasingly becoming inefficient in the face of today's agricultural needs. Hence, precision agriculture, which is a farming approach that utilizes modern technology, has emerged as a significant area of research and innovation. Although being a high priority in many developed countries, its adoption has been relatively slow within the country. We aim to introduce sustainable farming practices in Pakistan by introducing an AI-powered precision agriculture ecosystem by using autonomous drones and IoT sensors in an effort to help farmers improve their productivity, resource efficiency, and profitability while also reducing the harmful environmental impact.

1 Introduction

Agriculture has long been the backbone of Pakistan's economy, contributing approximately 19% to its Gross Domestic Product (GDP) and employing over 42.3% of the labor force [1]. However, the agricultural sector faces significant challenges, particularly in the context of food security, resource inefficiency, and environmental sustainability. Currently, more than 60% of Pakistan's population is food insecure, and a concerning 44% of children under five suffer from stunted growth [2]. Additionally, water scarcity and inefficient irrigation practices exacerbate the already critical situation, with about 50% of surface irrigation water lost due to inefficiencies [3]. This situation is direr considering Pakistan is among the top 10 water scarce countries in the world and agriculture consumes 90% of its freshwater resources.

The main cause of above-mentioned issues are traditional farming practices, which are inefficient, unable to meet the growing food demands, and harmful to the environment. Moreover, they do not take into account the issues unique to the present time, for example climate change, which is important to take into consideration.

Precision agriculture poses a solution to these problems. It utilizes technologies like geo mapping, remote sensing, variable rate technology, automated steering technology and satellite-positioning systems etc., to drive various improvements in agriculture, including crop health monitoring, crop yield estimation, pesticides detection, and irrigation optimization. Precision agriculture is an active area of research and innovation as it can potentially provide a solution to the global food crisis. Moreover, it can increase the profitability of agri-businesses through data-driven decision-making.

Our project, titled "AI-powered Precision Agriculture using Autonomous Drones and IoT Sensors," seeks to develop an AI-powered precision agriculture ecosystem to promote sustainable farming practices in Pakistan at both a micro and a macro level. We aim to harness the power of AI, advanced IoT technologies and a vast corpus of crop data, to help both common farmers and agri-businesses with their farming needs. We will provide a comprehensive set of features, which will include crop health monitoring, crop disease diagnosis and treatment recommendations, pesticides detection, irrigation optimization, and crop yield estimation. We will integrate autonomous drone technology to capture aerial imagery of farmlands, and to provide real-time detection and prediction capabilities. Moreover, we will utilize different IoT sensors to capture information related to soil's nutritional content, temperature, and humidity, which will help us develop more personalized recommendations for the farmers, which are both insightful and actionable. We will use Raspberry Pi for performing edge computing, and a cloud infrastructure for deploying our models and for storing the data, which the integrated devices will capture.

2 Related work

Precision agriculture is increasingly becoming mainstream in recent decades due to the growing agricultural demands. Several studies have explored the application of AI, IoT, and drones in agriculture, in an effort to determine their positive impacts.

2.1 Research Articles

We have explored various research articles related to precision and/or smart agriculture in an effort to understand the machine learning approaches, which scientists are currently applying in this field.

We came across a study, which provides a comprehensive survey of the tools and technologies, which scientists are employing around the world for the purpose of precision agriculture. The paper mentioned five main technology categories, which are in use [4]. They include Geomapping, Remote Sensing, Automated Steering Technology, Variable Rate Technology, and Satellite positioning systems. Their observations about collecting data from autonomous drones and IoT sensors, and transmitting it to the cloud were particularly beneficial.

Another group of researchers explored the use of Sentinel-2 satellite imagery to monitor potato fields in Lebanon, demonstrating the use of remote sensing technologies in precision agriculture [5].

The National Agriculture Imagery Program (NAIP) dataset has also been instrumental in advancing precision agriculture research. We explored an article of research which reviewed the use of NAIP imagery for land cover classification and feature extraction, discussing how high-resolution aerial imagery helps monitor agricultural fields over time [6].

We are exploring several other resources as well.

2.2 Datasets

2.2.1 Agriculture-Vision Dataset

This dataset contains 94,986 high-quality aerial images collected from farmlands in the U.S. The images contain both RGB and NIR (near infrared) channels, and support a high resolution, reaching as much as 10cm per pixel [7]. We can utilize this dataset for the purpose of semantic segmentation of the common patterns found in agricultural lands.

2.2.2 National Agriculture Imagery Program (NAIP)

NASA curated this dataset, and it contains high-resolution aerial imagery collected during the growing season of agricultural lands across the US [8]. This dataset is widely used, studied, and expanded upon for various use cases and applications, for example land management, farm monitoring, and precision agriculture.

2.2.3 Detecting Diseases in Crops (Roboflow)

This project contains datasets containing images of crops affected by various pest-related diseases. The featured infested crops included tomatoes, beans and strawberries among others [9]. We can utilize these datasets to train models for the purpose of pesticides detection.

2.2.4 Agricultural Crops Image Classification

This dataset contains images of 30 different types of crops, such as rice, maize, and sugarcane. We can utilize this dataset in part to develop features like crop disease diagnosis [10].

As our work progresses, we will explore, and utilize other datasets as well. They may be varied in their source, size, and structure as we aim to train several models for different features. We might also create our own annotated dataset from the imagery collected from our autonomous drones, and/or user applications.

2.3 Existing/Similar Products

2.3.1 Farmdar

A start-up using AI & space technologies at scale for driving sustainability in agriculture [11]. They have covered over 500 million acres of land through their autonomous drone and satellite technology. However, they only cater to large organizations and agribusinesses, and do not emphasize products, which would be feasible for a common farmer. We wish to create an all-rounded product set, which is inclusive for different levels of contributors to the agricultural sector.

2.3.2 کسان مددگار

A mobile app for farmers for the purpose of easier knowledge discovery and support. The parent company behind this app is Concave-Agri, which is also a start-up focused promoting precision agriculture practices [12]. While, it does provide a simple, yet intuitive interface in Urdu, useful information, for example harvesting times of common crops within the country, and a carefully curated FAQ section, it lacks features like crop health monitoring, and real-time pesticides and crop diseases detection. Moreover, it does not provide personalized recommendations to the farmers. Nor, does it have an audio-based chat-bot. We want to overcome these shortcomings, by adding these features to our apps to provide an all-in-one farming solution.

3 Project Rationale

Pakistan faces huge challenges in the form of food scarcity, and malnutrition. With the highest population growth rate of 1.96 in South Asia, Pakistan's population is only expected to rise at a rapid pace, and these problems are highly likely to be escalated. According to the UN World Food Program, about 20.5% of Pakistan's population is under-nourished [2]. Precision agriculture can help alleviate the food shortage problem by maximizing crop yield through a host of tools like crop health monitoring, and pesticides detection. Another severe issue is that of water shortage. Pakistan is a water-scarce country, and a big percentage of water is lost in irrigation due to inefficient farming practices. Precision agriculture can help in this regard as well. We can utilize it to optimize irrigation practices, by informing the farmers about which areas within the farmland require more water as compared to others. A wide-scale adoption of such tools has a potential to reduce water wastage in irrigation by a considerable percentage. Pakistan is facing climate change and its implications could be devastating if we do not take proper pro-active measures. We must conserve all the resources being used in the agricultural sector whether water or fertilizers.

The bigger and far-reaching aim of this project is also to provide a platform, which can help educate the common farmers about the changing agricultural landscape, and to equip them with the technological tools required to improve their farming practices. Empowering the farmers will be one of the crucial first steps towards building a food secure Pakistan.

3.1 Aims and Objectives

Through the scope of this project, we aim to solve these issues using smart precision agriculture by:

- Developing tools for crop health monitoring to maximize farming yield.
- Optimizing irrigation practices to reduce water wastage.
- Estimating crop yield.
- Providing actionable insights and personalized recommendations to the farmers.
- Promoting data-driven decision making in farming practices.

3.2 Scope of the Project

The scope of this project encompasses several key aspects that we must successfully implement to ensure expected delivery. The specific goals include the development of robust ML models, which will perform various tasks like crop monitoring, irrigation optimization, and predictive analysis. Moreover, developing intuitive and user-friendly user applications will be another instrumental goal. The following are the main deliverables:

- Robust machine learning models trained on huge and quality agricultural imagery datasets, which can distinguish between healthy and unhealthy crops, can detect pesticides, can determine areas requiring more or less water and optimize irrigation practices accordingly, can diagnose crop diseases and provide most beneficial treatment options and overall can provide actionable insights to the farmers.
- Intuitive and easy-to-use mobile and web applications, which contain useful features for both common farmers and large agri-businesses.

3.3 Success Criteria

The criteria for our successful project are as follows:

- The solution must enable real-time crop and field analysis using images and videos captured by the drone.
- The system should perform accurate predictive analysis and health diagnostics of crops, utilizing advanced AI models.
- The solution must be integrated with a user-friendly application that displays valuable insights on crop health, growth trends, and actionable recommendations.
- The application dashboard should provide the user with clear and useful insights derived from the drone data to support informed decision-making in the field.

4 Proposed Methodology and Architecture

We have identified the following main components or entities, which will interact among themselves to bring the application to completion:

- Farm Field Sensors and Autonomous Drone

- Edge Computing (Raspberry Pi)
- Cloud Infrastructure
- User Applications (Mobile and Web)

4.1 Level 0 Data Flow Diagram

The Level-0 DFD or Context diagram displayed below provides an abstract, high-level view of the entire system with the main external entities and the data flow.

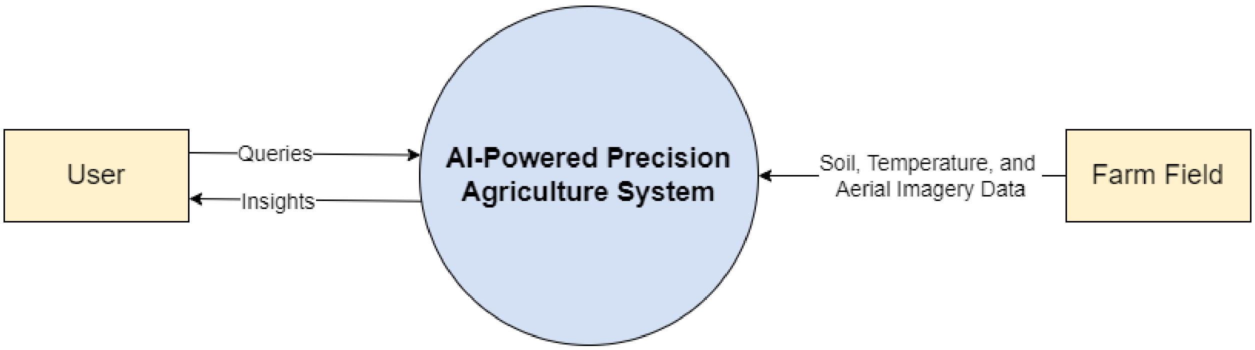

Fig 1: Level 0 DFD

4.2 Level 1 Data Flow Diagram

The Level-1 DFD displayed below is also providing a general overview, but the main process from the Level-0 DFD is broken down into multiple sub-processes, and data storage is conceptualized in addition to data flow.

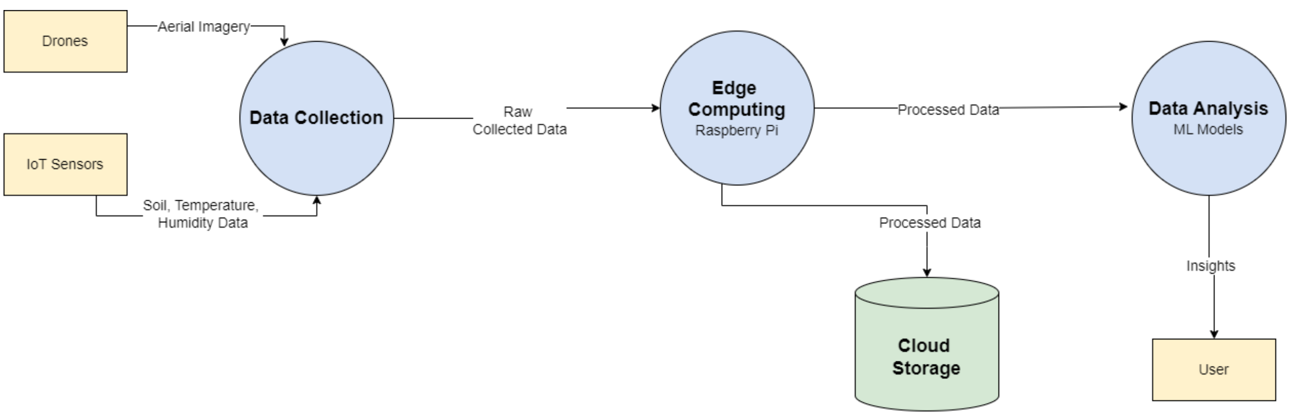

Fig 2: Level 1 DFD

4.3 System Architecture Diagram

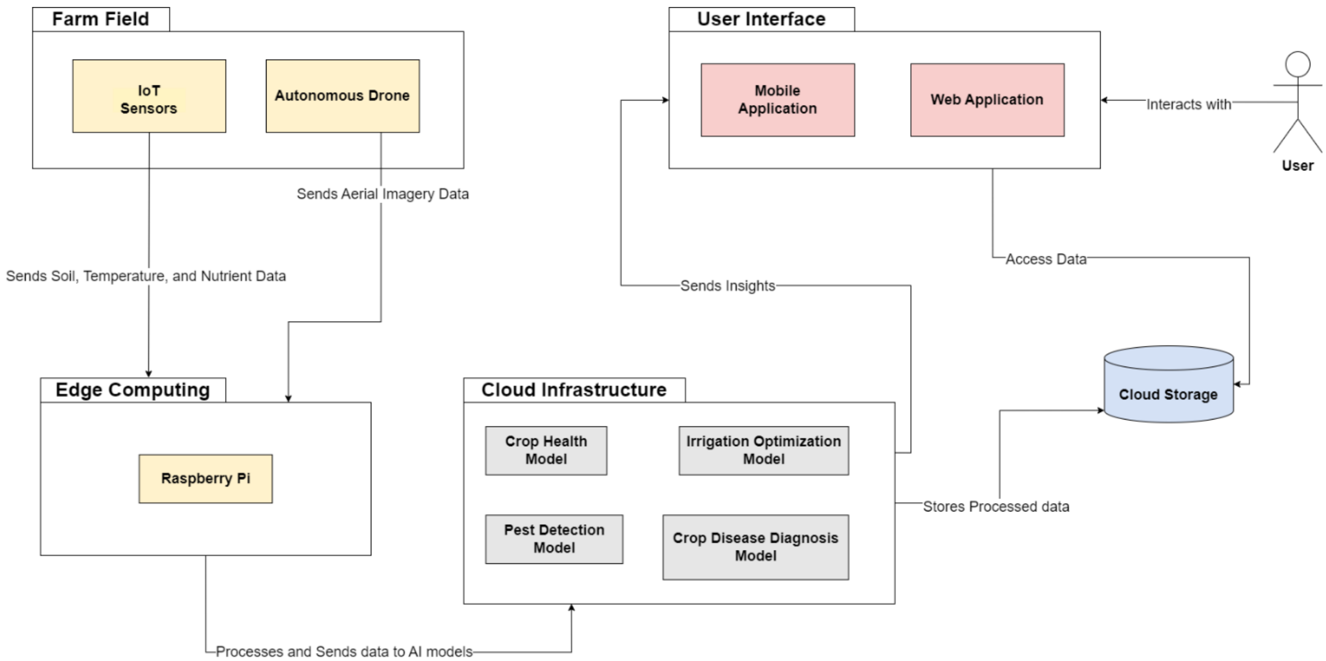

Fig 3: Architecture Diagram

5 Individual Tasks

Below is a tabular description of how we will divide the tasks individually, and what will be the tentative time for each task:

Team Member	**Activity**	**Tentative Time Period**
Ayesha Gull & Muhammad Umer Farooq	Project Planning	1st October – 31st October
Muhammad Umer Farooq	Hardware Setup & Configuration	1st October – 31st October
Ayesha Gull	Data Collection & Preparation	1st November – 30th November

Muhammad Umer Farooq	Data Pre-processing	1st November – 30th November
Ayesha Gull & Muhammad Umer Farooq	Model Development	1st December – 15th January
Ayesha Gull & Muhammad Umer Farooq	Edge Computing Integration	16th January – 1st February
Ayesha Gull & Muhammad Umer Farooq	Cloud Infrastructure & Backend Development	2nd February – 17th February
Ayesha Gull	Frontend Development	18th February – 25th March
Muhammad Umer Farooq	Cloud Infrastructure & Backend Development & Model Refinement	18th February – 25th March
Ayesha Gull & Muhammad Umer Farooq	Testing & Validation	26th March – 15th April
Ayesha Gull & Muhammad Umer Farooq	Deployment	16th April – 28th April
Ayesha Gull & Muhammad Umer Farooq	User Testing	29th April – 25th May

Tab 1: Individual Task Distribution

6 Tools and Technologies

We have identified the following hardware and software tools, which we will utilize for implementing our project:

6.1 Hardware Tools:

- DJI Autonomous Drone with SDK support
- IoT Sensors
- Raspberry Pi

6.2 Software Tools:

- Python (TensorFlow, Open CV)

- Google Cloud IoT Core
- Development Frameworks and Databases (React, Firebase etc.)

We may introduce other tools and modify or replace the existing ones if the need for doing so arises as the project unfolds.

6.3 Object Detection Models

6.3.1 YOLOv10 (You Only Look Once - Version 10)

YOLO is a known object detection model. It is often in use for its object detection capabilities in the real time. It divides the image into a grid and predicts bounding boxes and class probabilities directly. This allows it to perform its operations extremely fast. This speed and efficiency make it ideal for real-time applications like drone-based crop monitoring, where we need quick identification of objects like pests or diseases in agricultural fields. We will primarily use YOLOv10 for our project due to its high accuracy and speed, particularly in edge computing environments with limited resources [13].

6.3.2 Faster R-CNN (Region-based Convolutional Neural Networks)

Faster R-CNN is a two-stage object detection model. It first identifies regions of interest (RoIs) in an image and then classifies objects within those regions. While it is slower than YOLO, it offers high precision, making it useful for applications where accuracy is more critical than speed. For our system, we could experiment with Faster R-CNN for detailed analysis when processing large agricultural datasets [14].

6.3.3 SSD (Single Shot Multi-Box Detector)

SSD is another popular real-time object detection model that balances speed and accuracy. Unlike Faster R-CNN, SSD performs object detection in a single pass, making it faster. It is a good choice for resource-constrained environments like drones or Raspberry Pi devices. Although not as fast as YOLO, SSD can be experimented with in our project for detecting multiple objects (such as various types of pests or plant conditions) simultaneously in large agricultural images [15].

6.3.4 RetinaNet

RetinaNet is popular for its high accuracy, especially in detecting objects that vary in size. It uses a feature pyramid network to detect objects at different scales and a focal loss function to focus on harder-to-detect objects. This could be particularly useful in our project for detecting smaller or more subtle features in crop fields, like early-stage diseases or small pests, which might not be as noticeable to faster models [16].

7 Gantt chart

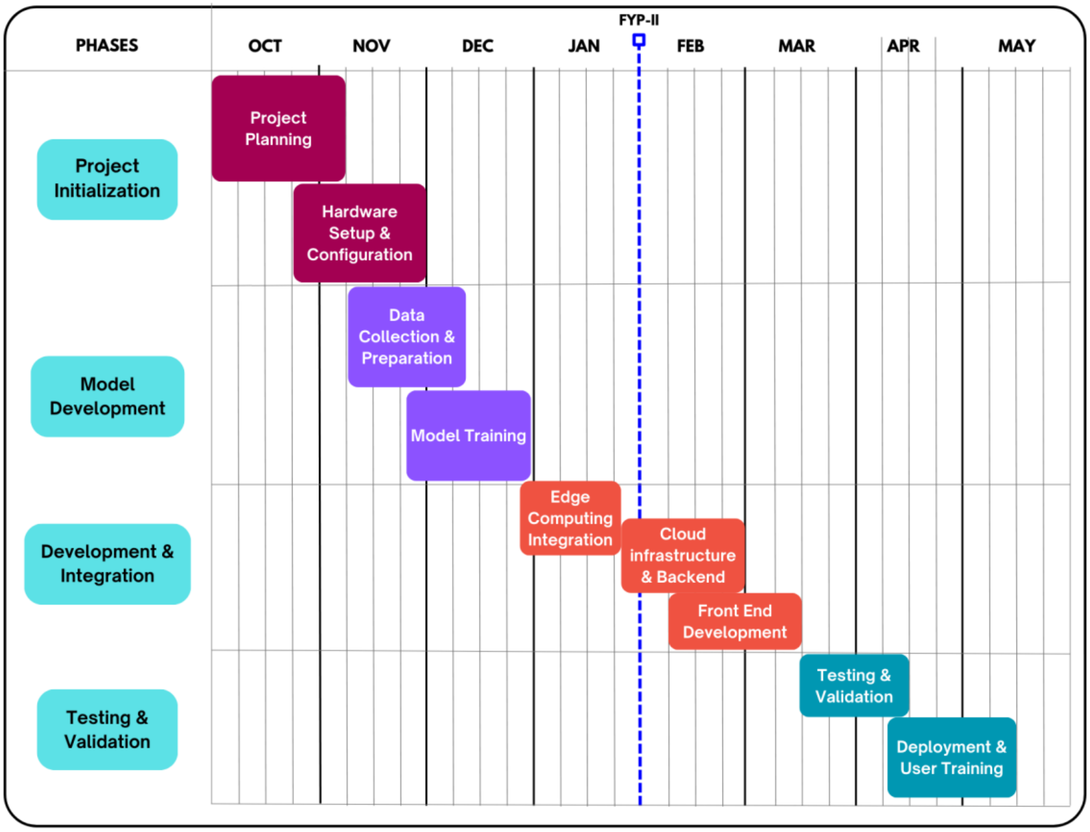

Fig 2: Gantt chart

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Appendix A

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