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A Technical Seminar Report on

"Crop Recommendation and Disease Prediction using IOT and AI"

Submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF ENGINEERING
IN
COMPUTER SCIENCE AND ENGINEERING

Submitted by:

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Certificate

This is to certify that Technical Seminar entitled **“Crop Recommendation And Disease Prediction Using IOT And AI”** is work carried out by Mr. Somashekhar Guddapur (2AG22CS126) in partial fulfillment of the requirements for the award of the degree of **Bachelor of Computer Science & Engineering under Visvesvaraya Technological University, Belagavi** during the year 2025-2026. It is certified that all the correction/suggestion indicated for internal assessment have been incorporated in the report. The Final Year Seminar report has been approved as it satisfies the academic requirements in respect of Final Year Seminar work prescribed for the Bachelor of Engineering degree.

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Vision of the Department
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PEO5: Understand the efficacy of life-long learning, professional ethics and practices, so that they may emerge as global leaders.

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ABSTRACT

Although farmers are the backbone of this emerging country, they face challenges in their daily lives related to finances and finding a place to work. These farmers search far and wide for the ideal location, climate, crop, and so on. By anticipating possible illnesses through image processing and suggesting appropriate crops based on real-time sensor data, you may use IOT and AI technology to improve agricultural operations. Used Sensors: Use sensors for pH, temperature, and soil moisture to gather important information from the agricultural field. Data Transmission: Create a communication network so that sensor-generated data may be sent to an AI model that has already been trained for analysis. Training AI Models: In order to precisely estimate the ideal crop options based on temperature, sand moisture, pH levels, give priority to training the AI model with pertinent data. Crop Recommendation: Create algorithms in the AI model that take into account the sensor data that has been collected in order to suggest the best crops yield in a certain location. An innovative answer to the growing need for effective and sustainable farming methods is the fusion of Internet of Things (IOT) with artificial intelligence (AI) technology. Thus the result of the project is to find a resolution for cost loss issue. In order to improve agricultural operations, this research uses real-time sensor data to select appropriate crops and forecast probable illnesses..

Keywords*: Deep learning, Machine learning, Algorithm and Technologies, Internet of things (IOT), Plant disease, Crop selection*

CHAPTER 1

INTRODUCTION

1.1 Brief of Technology

The “Crop Recommendation and Disease Prediction using IoT and AI” system integrates Internet of Things (IoT) and Artificial Intelligence (AI) to enhance smart farming. IoT devices such as sensors and microcontrollers (Arduino, Raspberry Pi, ESP32) collect real-time data on soil moisture, temperature, humidity, and pH, which are transmitted to cloud platforms for processing. AI and Machine Learning algorithms analyze this data to recommend the most suitable crops for given conditions, while Deep Learning models (like CNNs) identify plant diseases from leaf images. Cloud computing and data analytics enable remote data storage and visualization through web or mobile applications, providing farmers with real-time insights and actionable recommendations. This technology helps improve productivity, resource efficiency, and early disease detection for sustainable agriculture.

Technology used in Crop Recommendation and Disease Prediction using IoT and AI:

1. **The Internet of Things (IoT):** Plays a vital role in collecting real-time data from the agricultural environment. Various sensors are used to measure important parameters such as soil moisture, pH level, temperature, humidity, and light intensity. Microcontroller boards like Arduino, Raspberry Pi, or ESP32 are employed to collect and transmit this sensor data. Communication technologies such as Wi-Fi, LoRa, GSM, or Bluetooth are used to send the collected data to cloud servers or local systems for further processing. Cloud platforms like ThingSpeak, AWS IoT, and Google Cloud IoT are then used to store, analyze, and visualize the data. The main purpose of IoT in this system is to continuously monitor farm conditions and provide accurate environmental inputs that support crop recommendation and disease prediction models.

2. **Artificial Intelligence (AI):** It is utilized for data analysis, prediction, and decision-making in smart farming applications. Machine Learning (ML) algorithms such as Random Forest, Decision Tree, and Support Vector Machine (SVM) analyze environmental and soil data to recommend the most suitable crops based on soil type and weather conditions. Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), are employed to analyze leaf images and automatically detect and classify plant diseases. The AI models are trained using large datasets collected from agricultural research centers or publicly available image databases like PlantVillage. The main purpose of AI in this system is to provide real-time recommendations and early disease alerts, enabling farmers to improve crop yield, maintain plant health, and make informed agricultural decisions.

1.2 Problem Statement & Research Gaps

Traditional farming relies on guesswork, leading to poor yields and delayed disease detection due to the lack of real-time environmental data. Integrating IoT and AI enables continuous field monitoring, crop recommendation, and early disease prediction for smarter, data-driven farming.

- **Gap 1: Lack of Real-time Integration**: Most existing systems focus either on crop recommendation or disease detection, but few integrate both using real-time IoT data.

- **Gap 2: Limited Local Dataset Availability:** Many AI models are trained on global datasets that do not accurately represent local soil types, climatic conditions, or regional crops.

- **Gap 3: Connectivity and Cost Issues:** In rural areas, unstable internet connectivity and the high cost of IoT deployment limit system scalability.

- **Gap 4: Low Accuracy in Disease Detection:** Traditional image-based models struggle with detecting multiple diseases under varying light, background, or leaf conditions.

- **Gap 5: Farmer Accessibility:** Many developed solutions lack a user-friendly interface or language support that can make them easily usable by farmers with limited technical skills.

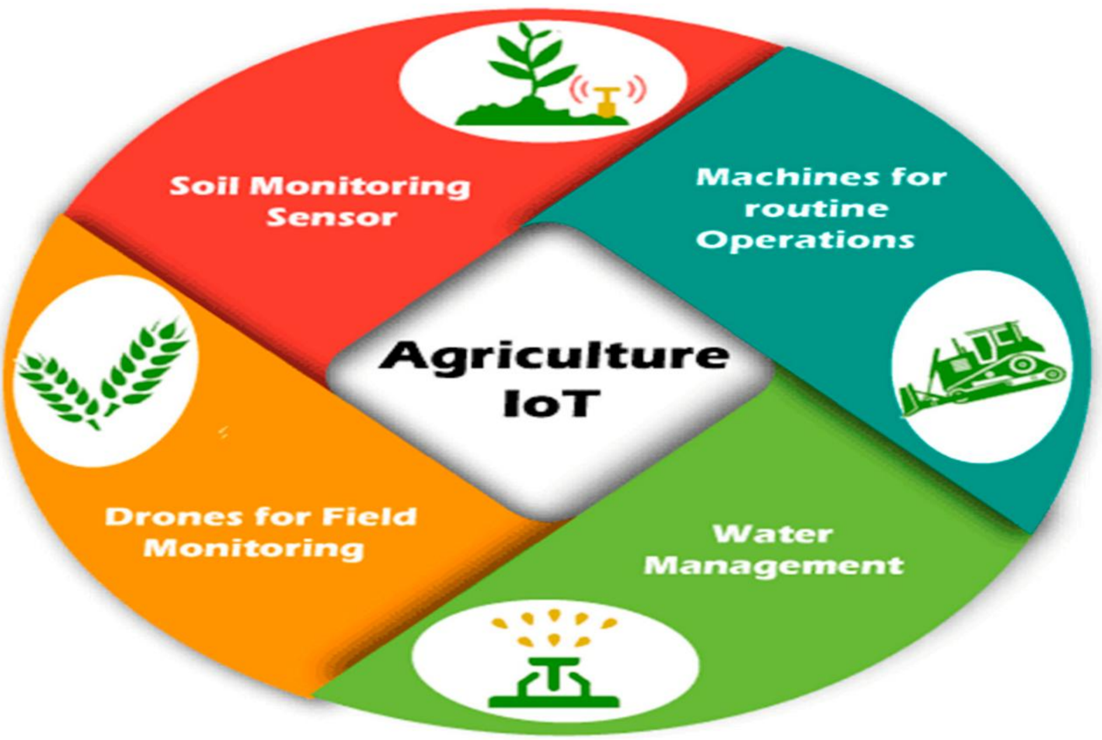

Fig 1.1 Agriculture IOT

1.3 Contributions of this Study

The main contributions of this work are:

1. **Real-time Monitoring:** Uses IoT sensors to continuously measure soil moisture, pH, temperature, and humidity.

2. **Smart Crop Recommendation:** Employs AI and ML algorithms to suggest the most suitable crops based on environmental and soil data.

3. **Early Disease Detection:** Utilizes deep learning (CNN) models to identify and classify plant diseases from leaf images.

4. **Data-driven Decision Making:** Integrates IoT data with AI analytics for accurate and automated farm management.

5. **User-friendly Interface:** Provides farmers with an easy-to-use mobile or web application for real-time insights and alerts.

6. **Increased Productivity:** Helps optimize crop yield and resource usage through timely and intelligent recommendations.

CHAPTER 2

LITERATURE SURVEY

The development of our integrated model is built upon previous research in traffic flow theory and neural network applications.

[1] **Title:** Using Deep Learning for Image-Based Plant Disease Detection

Author: S. P. Mohanty, D. P. Hughes, M. Salathe

Journal: Frontiers in Plant Science

Published year: 2016

Model/Tech stack used: Deep Convolutional Neural Networks

Summary: The authors trained deep convolutional neural networks on the PlantVillage dataset to classify 14 crop species and 26 disease classes (including healthy).

Advantages: Demonstrated high accuracy and established a public benchmark (PlantVillage), Simple end-to-end pipeline

Disadvantages: Trained on controlled images; performance drops on real field images, Single-image classification ignores temporal/sensor context.

[2] **Title:** A Systematic Review of IoT Solutions for Smart Farming

Author: Emerson Navarro, Nuno Costa, António Pereira (et al.)

Journal: Sensors (Basel)

Published year: 2020

Model/Tech stack used: Summarizes IoT devices,communication protocols, cloud platforms and common data processing patterns.

Summary: This systematic review analyzes published IoT solutions for smart farming, catalogues common sensors, network architectures, cloud/edge deployments, and identifies practical barriers and research trends toward edge/cloud hybrid systems.

Advantages: Comprehensive taxonomy of IoT hardware, protocols and architectures for agriculture, Identifies deployment challenges and research directions.

Disadvantages: Review paper — does not present new empirical system results, rapidly

evolving field — some hardware/platform details date quickly after publication.
Source:

[3] **Title:** Using Deep Transfer Learning for Image-Based Plant Disease Identification.

Author: J. Chen et al.

Journal: Computers and Electronics in Agriculture

Published year: 2020

Model/Tech stack used: Transfer learning with pre-trained CNNs, data augmentation and fine-tuning approaches.

Summary: The work investigates transfer learning of modern CNN architectures for plant disease detection and shows that fine-tuning pre-trained networks improves performance, especially when labelled domain data are limited; suggests transfer learning as a practical approach to adapt models to new crops or small datasets.

Advantages: Efficient use of limited labelled data; better generalization than training from scratch, Practical for researchers who lack large domain-specific datasets.

Disadvantages: Still sensitive to domain shift: source (ImageNet) → target (leaf images) mismatch and field image variability,Fine-tuning choices and augmentation strategies require empirical tuning.

[4] **Title:** Disease detection in tomato leaves via CNN (comparative study)

Author: V. González-Huitrón et al.

Journal: Computers & Electrical Engineering

Published year: 2021

Model/Tech stack used: Comparative evaluation of several CNN architectures on tomato leaf disease datasets; emphasis on preprocessing and evaluation metrics.

Summary: This paper evaluates multiple CNN models for tomato disease classification, reporting performance differences and discussing the influence of preprocessing on accuracy. It highlights practical steps to improve model robustness for a specific crop.

Advantages: Direct comparative evidence about which architectures work better on a specific crop (tomato), Discusses preprocessing and evaluation best practices.

Disadvantages: Focused on a single crop — limited generalizability across crops, Benchmarks may still use curated/controlled images rather than field captures.

[5] **Title:** IoT-based Crop Monitoring and Disease Detection (prototype / applied study)

Author: X. Yin, G. Wu, J. Wei, Y. Shen, H. Qi, and B. Yin

Journal: Conference / institutional repositories and applied journals

Published year: 2023-2024

Model/Tech stack used: ESP32/ESP32-CAM or Raspberry Pi for image capture; Arduino/ESP32 for sensor collection

Summary: These applied works build end-to-end prototypes that combine low-cost IoT nodes for continuous sensing with image-based CNN classifiers for disease detection. Many use ESP32-CAM modules and Raspberry Pi gateways, pushing toward on-device or near-edge inference to reduce latency and bandwidth.

Advantages: Demonstrates feasibility of full-stack systems deployable in small farms,Practical lessons on hardware selection, power management, and network trade-offs.

Disadvantages: Most are pilot/prototype scale with limited long-term, multi-region validation, Real-world robustness, scalability, and farmer-centric usability studies are often missing

[6] **Title:** A Smart Agriculture: A Comprehensive Survey on IoT-Enabled Plant Disease Detection and Agricultural Automation

Author: T. Thilagavathi, L. Arockiam, I. Priya Stella Mary

Journal: International Journal of Information Technology, Research & Applications

Published year: 2024

Model/Tech stack used: Survey of IoT devices + ML classification techniques

Summary: Reviews many techniques for plant disease detection in agriculture, focusing on how IoT integration has evolved and current challenges.

Advantages: Good broad overview of IoT + AI in agriculture; helps identify challenges and research gaps.
Disadvantages: It’s a survey (not empirical) so lacks new experimental results; may cover many technologies superficially rather than in depth.

[7] **Title:** Smart Plant Disease Management: Integrating Deep Learning and IoT for Rapid Diagnosis and Precision Treatment

Author: Prameeta Pai, Shubhan S. Bhat, Lavanya G, Shabeena A, Rakshitha G

Journal: Int. J. Intelligent Systems & Applications in Engineering

Published year: 2024

Model/Tech stack used: IoT sensing + deep learning (image-based) for disease detection

Summary: Explores how IoT devices collect real-time crop health and environmental data, and how DL models analyse images for early disease detection

Advantages: Combines sensor + image data; timely for precision treatment.

Disadvantages: Reportedly covers architecture but may not have long-term field validation; might be limited to specific crops/environments.

CHAPTER 3

METHODOLOGY

Our methodology is organized into a synergistic system that handles user queries, processes data, estimates traffic density, and composes a natural language response.

3.1 System Architecture

The entire system workflow is divided into three primary phases, as shown in the workflow:

1. **Field Layer (Edge Sensors & Cameras):**
    - Soil sensors: moisture, pH, EC/nutrients, temperature.
    - Environmental sensors: air temperature, humidity, light (PAR), rainfall/wind (optional).
    - Imaging: smartphone, tower camera, or ESP32-CAM for leaf/plant photos.
    - Local microcontroller/edge node: Arduino / ESP32 / Raspberry Pi to read sensors and control actuators (optional actuators: irrigation valves, fertigation).

2. **Edge Gateway / Preprocessing Layer:**
    - Aggregates sensor data; performs lightweight preprocessing (filtering, normalization).
    - Runs lightweight inference for immediate alerts (optional tinyML models) or compresses images before upload.
    - Connectivity bridge (LoRaWAN gateway, GSM modem, Wi-Fi router, or NB-IoT).

3. **Backend / Cloud Layer:**
    - Ingestion API: receives sensor telemetry and images (REST/gRPC/MQTT).
    - Stream processor: real-time processing, validations, anomaly detection (Kafka / RabbitMQ / AWS Kinesis).
    - Storage: time-series DB for telemetry (InfluxDB, TimescaleDB), object storage for images (S3), relational DB for metadata (Postgres).
    - Model Serving: two main services:
        1. Crop Recommendation Service — ML model(s) (Random Forest / XGBoost / Neural Net) that accept soil + weather + historical data → recommended crops and sowing windows.
        2. Disease Detection Service — DL model (CNN: ResNet/MobileNet/EfficientNet) that accept images → disease class + confidence + heatmap (Grad-CAM).
    - Model Training Pipeline: data labeling, augmentation, training (TensorFlow/PyTorch), CI for retraining, model registry (MLflow), and A/B testing.
    - Analytics & Rules Engine: business rules for alerts, thresholding, irrigation scheduling, and integration with weather forecasts.

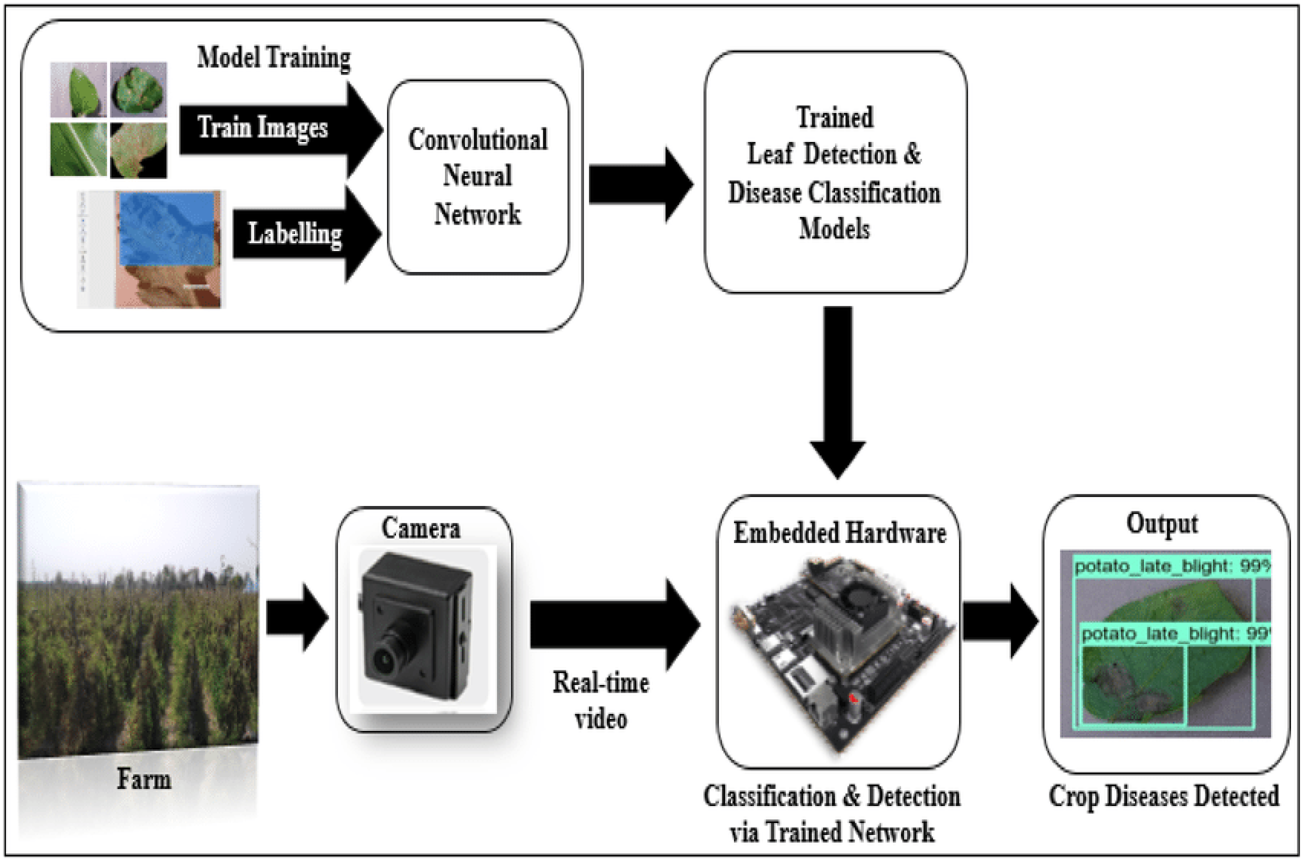

Fig 3.1: System Architecture

3.2 Data Pre-processing

- Sensors & camera capture telemetry and images periodically or on event.
- Edge node preprocesses (denoise, compress, rescale images, basic validation) and sends via MQTT/HTTP to Gateway.
- Gateway forwards to cloud ingestion endpoint (MQTT broker / REST API).
- Ingestion → stream processor: validates, timestamps, stores telemetry to time-series DB; images to object store.
- Telemetry + weather + soil history → Crop Recommendation Service → store recommendation & notify user.
- New image → Disease Detection Service → returns label + confidence + bounding/heatmap; if confidence > threshold or critical disease → trigger alert.
- All predictions logged for retraining; farmer feedback (confirm/deny) is captured for label improvement.
- Model retraining pipeline consumes labeled data, trains new models, performs validation, and updates model registry and production endpoint via canary/A/B rollout.

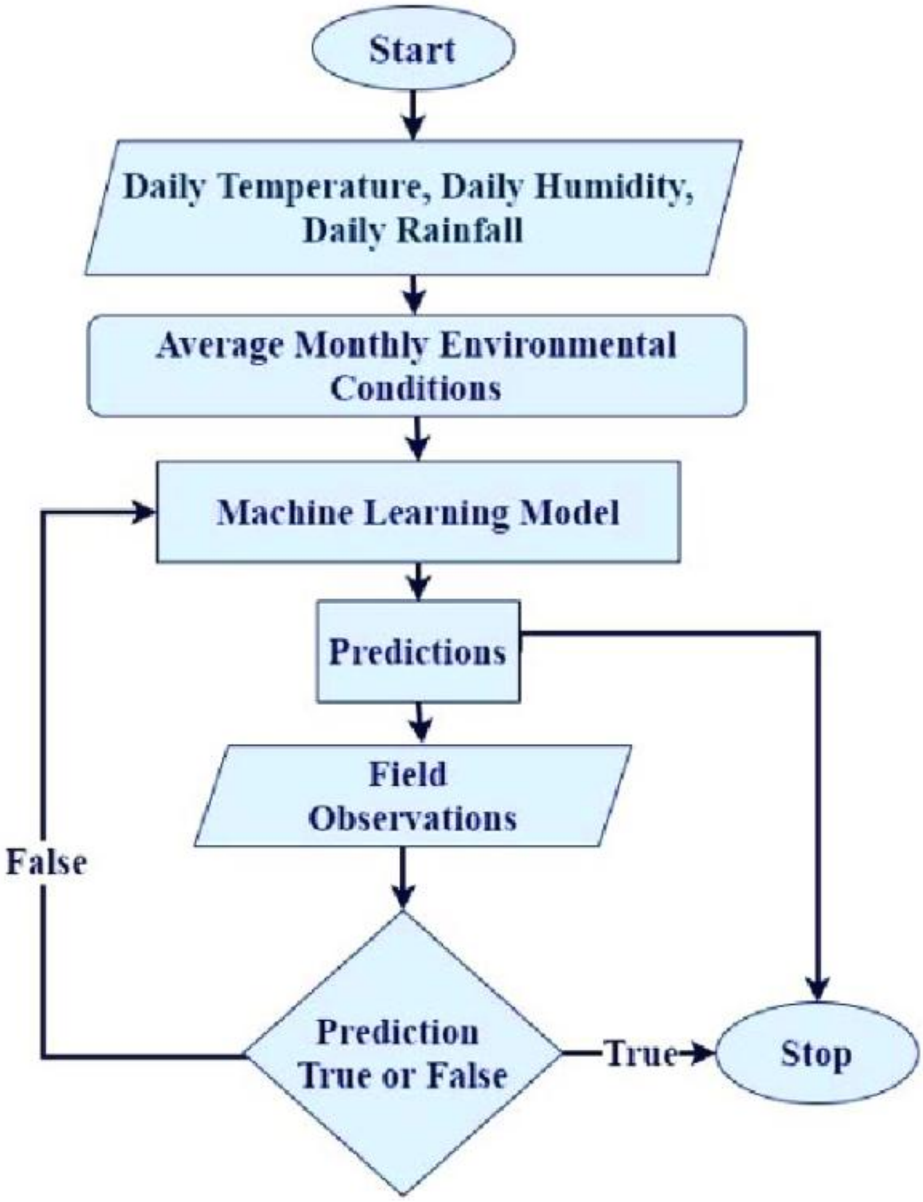

Fig 3.2: Flow chart for Data Pre-processing

3.3 Suggested tech stack (practical)

- **Edge & Devices:** ESP32, Arduino, Raspberry Pi, LoRaWAN nodes, solar power kits.
- **Connectivity:** MQTT over TLS, HTTPS REST, LoRaWAN network server (The Things Network) or NB-IoT for remote areas.
- **Cloud / Backend:**
  - Ingestion & Stream: MQTT broker (EMQX / Mosquitto), Kafka / AWS Kinesis.
  - Storage: InfluxDB/TimescaleDB + PostgreSQL + S3 / MinIO.
  - Model serving: TensorFlow Serving or TorchServe, or serverless containers (AWS SageMaker Endpoints, Google AI Platform).
  - Training / MLOps: Kubeflow / MLflow / GitHub Actions; Docker & Kubernetes for orchestration.
- **Frontend:** React (web), React Native / Flutter (mobile).

- **Monitoring:** Prometheus + Grafana, ELK stack.
- **CI/CD:** GitHub Actions / GitLab CI, Terraform for infra as code.

3.4 ML model specifics & lifecycle

- **Crop Recommendation Model:** Inputs — soil features (pH, moisture, EC), historical yields, weather forecast, season. Model choices: Random Forest / XGBoost / MLP. Output: ranked crop recommendations with sowing window & expected yield. Retrain cadence: monthly/seasonal.
- **Disease Detection Model:** CNN (MobileNetV3 / EfficientNet-lite for mobile/edge). Output: disease label(s), confidence, attention map. Retrain cadence: continuous (weekly/monthly) as new labeled images arrive.
- **Evaluation metrics:** accuracy, precision/recall, F1, confusion matrix; for crop recs use top-k accuracy and economic impact simulation.

3.5 Data schema (short)

- **Telemetry (time-series):** { device_id, timestamp, sensor_type, value, unit, gps (lat,long), firmware_version }
- **Image metadata:** { image_id, device_id, timestamp, crop_type (optional), gps, file_path, resolution }
- **Predictions:** { prediction_id, model_version, input_id, output_label, confidence, timestamp }
- **Feedback:** { prediction_id, user_id, feedback_label, notes, timestamp }

3.6 Non-functional considerations

- **Latency:** Real-time alerts for disease detection — aim for <5s inference on edge, <500ms for telemetry. Use edge inference for critical alerts.
- **Bandwidth & Cost:** Compress images; send low-freq telemetry; use on-device inference for rural low-bandwidth scenarios.
- **Scalability:** Use stateless model serving behind autoscaling; Kafka for decoupling producers/consumers.
- **Resilience:** Local buffer on edge to handle connectivity outages (store & forward).
- **Privacy:** Minimize personally identifiable info; consider federated learning if privacy or bandwidth constraints exist.

3.7 Security & deployment notes

- Use mutual TLS for device authentication or device-level certificates.
- Device OTA updates for firmware and model weights (signed).
- Role-based access control for apps and admin consoles.
- Plan for backup & disaster recovery (DB snapshots, multi-AZ deployment).

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Experimental Analysis:

Here some analysis of data to know more about dataset. As already discussed it is the one of the best innovative technology in agriculture's field and yield. The fusion of IOT and Artificial Intelligence can change the traditional agriculture into modern technology. In this project dataset analysis plays vital role because there are two type of datasets are used. One of the dataset is used to predict crop suggestion for machine learning.

On the other hand, other dataset is used for deep learning that consists of images to predict disease. This below Fig 4.1 resembles the overall details of the dataset 1. It consists of Maximum value, Minimum value, Type of dataset, Missing value and DQ issues. By using this analysis can easily work with project to get perfect result

	Data Type	Missing Values%	Unique Values%	Minimum Value	Maximum Value
NITROGEN	int64	0.000000	6	0.000000	140.000000
PHOSPHORUS	int64	0.000000	5	5.000000	145.000000
POTASSIUM	int64	0.000000	3	5.000000	205.000000
TEMPERATURE	float64	0.000000	NA	8.825675	43.675493
HUMIDITY	float64	0.000000	NA	14.258040	99.981876
PH	float64	0.000000	NA	3.504752	9.935091
RAINFALL	float64	0.000000	NA	20.211267	298.560117
CROP	object	0.000000	1		

Fig 4.1: Detail of Dataset1

Like analysis of Fig 4.2 for crop, all analysis is important to gather details. The phosphorus is the nutrients of crop that is mentioned in Fig 4.1. Here is the analysis of phosphorus that is Fig 4.2.

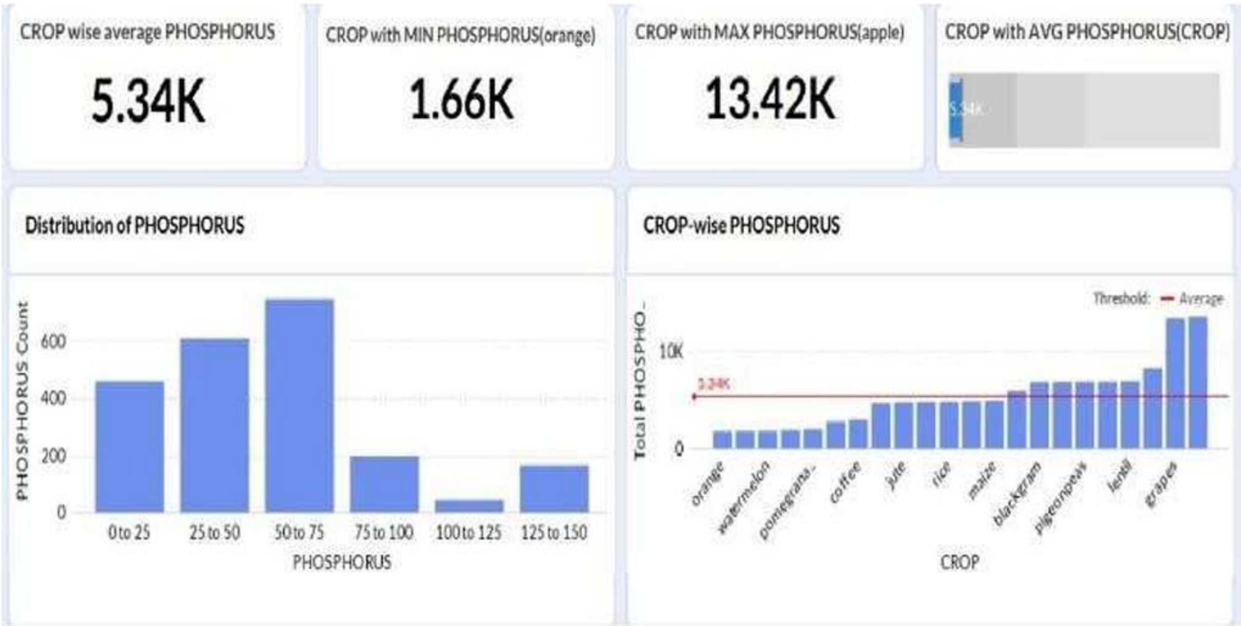

Fig 4.2: Analysis of Phosphorus

From the Fig 4.1, Display that it contains crop in the dataset. So Fig 4.2. Display what are the crops are presented and their percentage. Thus the analysis for the experiment was completed and mainly used for implementation.

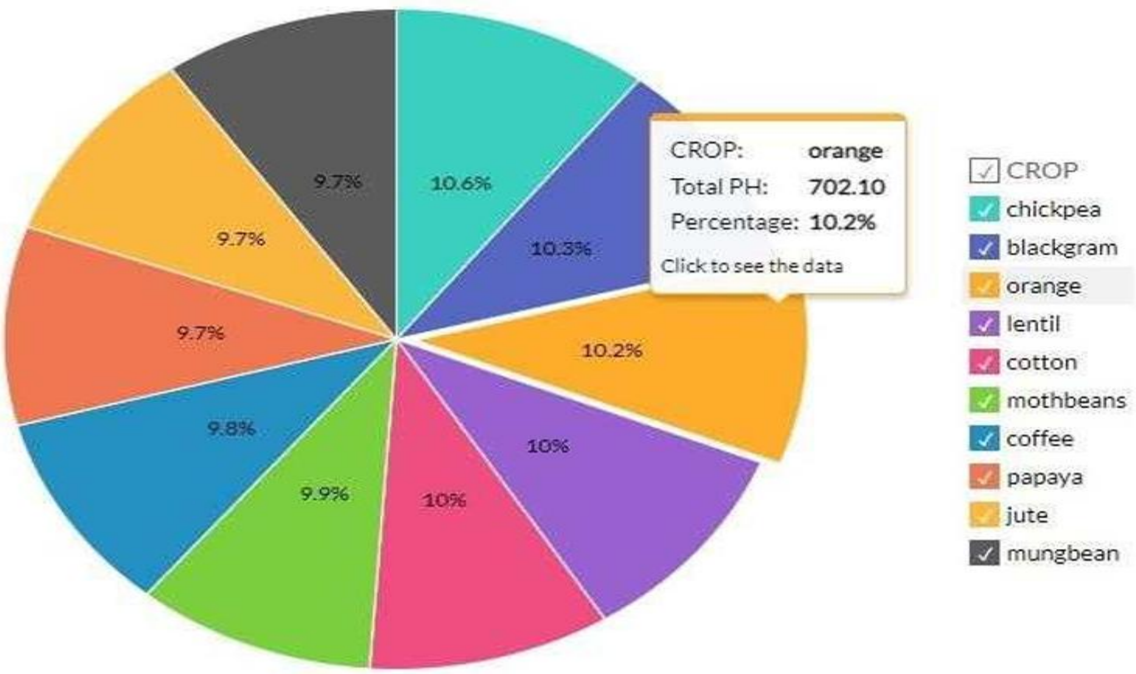

Fig 4.3: Pie chart of Crop

CONCLUSION

Conclusion

This agricultural project's use of IOT and AI technology marks a substantial leap in contemporary farming methods. The project's use of sensors to detect important field factors and AI algorithms to provide accurate crop suggestions guarantees an effective and data-driven farming strategy. Using image processing tools to detect diseases early improves the project's capacity to efficiently monitor and maintain crop health. Moreover, real-time communication is facilitated by the use of IOT, giving farmers instant notifications and advice. In the era of smart agriculture, this extensive and networked system facilitates efficient decision- making while also enabling farmers to maximize resource use, leading to the adoption of sustainable and intelligent agricultural techniques.

The fusion of IoT and AI for crop recommendation and disease prediction marks a significant step toward the future of smart and sustainable agriculture. By leveraging real-time data from IoT sensors and the analytical power of AI, farmers can make informed decisions about which crops to plant and how to manage them effectively. This technology not only enhances crop yield and quality but also minimizes resource wastage and reduces dependency on harmful chemicals. Early disease detection through AI-driven models helps prevent large-scale crop losses, ensuring food security and economic stability for farmers. Ultimately, IoT and AI together pave the way for precision agriculture, transforming farming into a more efficient, data-driven, and environmentally responsible practice that meets the growing demands of a global population.

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