International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

AI In Agriculture: Enhancing Smart Farming

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Abstract**-- Agriculture plays a critical role in ensuring food security and sustaining economic growth, yet traditional farming practices often rely on manual observation and experience-based decision-making, which can result in delayed disease detection, inaccurate yield estimation, and inefficient re-source utilization. To address these challenges, this paper presents a cloud-based Artificial Intelligence-driven Smart Agriculture system that integrates Internet of Things (IoT) sensors, machine learning algorithms, and deep learning techniques within a scalable cloud environment. The pro-posed system continuously collects real-time environmen-tal parameters such as temperature, humidity, and soil mois-ture using IoT devices and processes the data through pre-dictive models for crop suitability analysis and yield pre-diction. In addition, a MobileNetV2-based convolutional neural network is implemented for automated tomato leaf disease classification with confidence-based detection. The entire framework is deployed using Amazon Web Services (AWS) to ensure secure data storage, real-time process-ing, and scalable architecture. By combining IoT moni-toring, predictive analytics, and image-based disease de-tection into a unified platform, the proposed solution en-hances early disease identification, improves crop planning accuracy, and supports precision farming practices. Ex-perimental evaluation demonstrates reliable prediction per-formance, highlighting the effectiveness of the integrated smart agriculture system for sustainable farming applica-tions.**

Keywords**-- Smart Agriculture, Internet of Things (IoT), Deep Learn-ing, MobileNetV2, Crop Yield Prediction, Plant Disease Detection, Cloud Computing, Precision Farming.**

I. INTRODUCTION

Agriculture is one of the main pillars in supporting the world economy and meeting the food demands of the increasing world population. However, traditional agri-cultural practices involve monitoring and decision-making based on experience, which may result in inefficiencies and decreased agricultural production. Farmers face various difficulties, such as diseases, vagaries of nature, absence of real-time data, and improper use of resources. With the development of modern technology, agriculture is gradu-ally shifting to a smart and data-driven agriculture. Tech-nologies like Artificial Intelligence, Internet of Things, and Cloud Computing are allowing farmers to monitor crops, analyze environmental conditions, and make decisions.

The proposed system develops a smart farming platform which uses artificial intelligence to combine Internet of Things data and machine learning models and cloud computing re-sources. The system provides three functions which include crop yield prediction and crop suitability recommendations and plant disease detection through leaf image analysis. The solution operates on a scalable cloud system which en-ables users to access web applications that provide insights about agricultural productivity and agricultural loss reduc-tion.

A. Background of Smart Agriculture

Smart agriculture refers to the application of advanced tech-nologies in the form of digital technologies to improve agri-cultural activities to achieve better efficiency and higher crop production while maintaining sustainable environmen-tal conditions. This system makes use of Internet of Things sensors and artificial intelligence and data analytics and cloud computing to provide a system which allows agricul-tural operators to monitor and control their activities. For example, IoT devices can be used for collecting data such as temperature, humidity, rainfall, and soil moisture from the environment. Artificial intelligence models can be used for analyzing the data collected by the IoT devices, such as the detection of crop disease, prediction of crop yield, and suggestion of crops for planting, among other uses. Cloud computing can be used for storage of agricultural data, making it accessible from anywhere. Smart agricul-ture is an approach to farming that helps farmers shift from conventional manual farming to smart and automated farm-ing. This helps in effective decision-making, reduces waste of resources, and enhances crop yields.

B. Challenges in Traditional Farming

- Lack of Early Disease Detection: Crop diseases are often identified only after they spread widely, resulting in major crop damage and financial loss.
- Limited Access to Real-Time Data: Farmers often do not have access to accurate information about weather conditions, soil health, and crop growth.
- Inefficient Resource Management: Water, fertilizers, and pesticides are frequently used without proper mon-itoring, leading to wastage and environmental damage.

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- Manual Monitoring: Traditional farming relies heavily on manual observation, which is time-consuming and prone to human error.
- Uncertain Crop Planning: Farmers sometimes plant crops without analyzing soil conditions or environmental suitability, leading to reduced yield.

C. Role of IoT, AI, and Cloud Computing

IoT sensors can gather environmental data such as temper-ature, humidity, rainfall, and soil moisture. Farmers can better understand crop and soil conditions and respond ap-propriately with the aid of this information. AI, or artificial intelligence information in agriculture can be analyzed us-ing AI technologies like deep learning and machine learn-ing. AI can forecast crop yields based on environmental conditions, identify plant diseases using leaf images, and recommend appropriate crops for cultivation. Cloud Com-puting a scalable infrastructure for processing and storing massive volumes of agricultural data is made possible by cloud computing. The application, data storage, and ma-chine learning model deployment in the suggested system are all handled by cloud services. By combining these tech-nologies, a smart agriculture platform that boosts output and facilitates data-driven decision-making can be created.

D. Motivation of the Proposed Work

The motivation of the proposed work is to overcome the major problems that farmers face, such as delayed detection of diseases, inaccurate prediction of yield, and improper planning of crops. Crop diseases can cause a decline in agricultural production if they are not detected in time. Farmers do not have enough technical knowledge to detect diseases in crops. In addition, predicting the yield of crops and planning crops based on environmental conditions can be challenging. The proposed system intends to offer an effective solution to farmers through the integration of AI, IoT, and cloud technologies. The system assists farmers in increasing their productivity by providing early disease detection and precise yield forecasts and crop selection advice.

E. Paper Organization

The remainder of this paper is organized as follows. Section IV discusses related work. Section V describes the problem statement. Section VI explains the objectives of the system. Section VII presents the proposed system architecture. Sec-tion VIII explains system implementation. Section IX dis-cusses results and evaluation. Finally, Section X concludes the paper.

II. Related Work (Literature Review)

This section presents a concise review of existing research in smart agriculture, focusing on IoT-based monitoring sys-tems, machine learning approaches for crop prediction, cloud-enabled agricultural platforms, and deep learning techniques for plant disease detection. The discussion high-lights the methodologies adopted in prior studies, their con-tributions, and the limitations that motivate the need for an integrated and scalable smart farming framework.

A. IoT-Based Smart Agriculture Systems

Internet of Things (IoT)-based agricultural systems have at-tracted significant research interest due to their ability to enable real-time environmental monitoring and automated farm management. Several studies have proposed the deployment of sensors such as soil moisture sensors, temperature sensors, humidity sensors, and pH sensors to collect field-level data. These systems typically employ micro-controllers including ESP32, Arduino, or Raspberry Pi for data acquisition and utilize wireless communication protocols to transmit sensor readings to centralized dashboards or cloud platforms. Continuous monitoring of environmental conditions through IoT frameworks enhances irrigation efficiency and reduces dependence on manual supervision. Many implementations utilize threshold-based automation mechanisms in which irrigation systems are activated when soil moisture levels fall below predefined limits. While such approaches contribute to water conservation and improved crop management, the majority of IoT-based agricultural solutions emphasize data acquisition and visualization rather than predictive analytics. A notable limitation in existing research is the limited integration of intelligent decision-support mechanisms. Although environmental monitoring is achieved in real time, collected data is rarely processed using machine learning models for crop recommendation or yield estimation. Additionally, challenges such as network connectivity in rural areas, energy optimization of sensor nodes, scalability of deployments, and seamless cloud integration remain partially addressed.

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Therefore, IoT-based systems primarily provide monitoring capabilities and require integration with Artificial Intelligence-driven models and cloud infrastructure to enable comprehensive precision farming solutions.

B. AI and Machine Learning in Crop Prediction

Artificial Intelligence and machine learning are being used more and more in agriculture to help crops grow better and to make decisions based on data. Many studies have used machine learning algorithms like Linear Regression and Decision Trees to predict how much crops will grow based on things like weather and soil. These models look at things like how much it rains how hot or cold it is, what is in the soil and how much crops have grown in the past to guess how much they will grow. Using machine learning is better than ways of guessing because it is more accurate. Some people have also worked on systems that help farmers choose what crops to plant based on the weather and soil. This helps farmers use their resources better and reduces the risk of weather. Artificial Intelligence and machine learning are used in agriculture to make things better. Many systems that use Artificial Intelligence and machine learning in agriculture do not use new data from sensors. They use data and do not update when things change. Many studies compare algorithms and look at how accurate they are but they do not think about how to make the systems work in the real world. So even though Artificial Intelligence and machine learning are really good at predicting things they are not often used with data from the Internet of Things and cloud computing. We need a system that uses data from sensors and Artificial Intelligence to make decisions for farmers. Artificial Intelligence and machine learning, in agriculture need to be used with Internet of Things and cloud computing to work well.

C. Cloud-Based Agricultural Monitoring Systems

Cloud computing is a part of modern smart farming systems. It gives us a lot of space to store things lets us manage everything from one place. We can get to the information from anywhere. Some people have done research and connected sensors that use the internet to cloud platforms. This way we can always keep an eye on things like how wet the soil's how hot or cold it is and how much water is in the air. These sensors send the information they collect to cloud servers using ways of talking to each other. Then the information is stored, looked at and shown to us on websites or phone apps. Using cloud servers is really helpful because we can use much space as we need get more power to do things when we need it and get to the information from anywhere in the world.

Farmers and people who know a lot about farming can use cloud services to look at a lot of information that comes from sensors over the place. This makes it easier for them to see what is going on in the fields from away. We can also look at information from the past to see what happened and make plans for the future. Also, a lot of these systems do not do a job of keeping informa-tion safe making sure only the right people can get to it and making sure everything works well together. They often do not think about what might happen if something goes wrong or how to make the system bigger if we need to. As farm-ing becomes more digital we need to make sure the cloud services we use are safe and can handle a lot of informa-tion and that we can use intelligence to help us make good decisions. So, while cloud computing really helps make it easier to watch over farms and makes it possible to store a lot of information, we still need a system that combines sensors, predictive analytics and secure cloud computing to have a precision farming solution. We need to be able to use cloud computing and artificial intelligence to make farming better. Computing and artificial intelligence are important, for the future of farming.

D. Plant Disease Detection Using Deep Learning

Plant disease detection has become a lot better because of deep learning techniques. These techniques make it possible to automatically and accurately classify pictures of crop leaves. In the past people had to look at the leaves by hand or use methods to figure out what was wrong with them. This was often very time-consuming. Required a lot of expert knowledge. Now something called Convolutional Neural Networks or CNNs for short can look at pictures and recognize patterns that are hard to see. Many studies have used kinds of CNNs like VGGNet, ResNet, Inception and MobileNet to classify plant diseases. They use something called transfer learning, which means they use models that have already been trained on sets of pictures. This helps them be more accurate and work faster. These models have been tested on sets of pictures that're available to the public and they can classify many kinds of crop diseases very well. Some of these models like MobileNet are very good because they are small and can work well on devices that're not very powerful. MobileNet uses something called depthwise separable convolutions, which makes it work efficiently. This makes it very good for use in real-time systems that help farmers or in systems that work on devices or in the cloud. Even though these systems can classify diseases well they are often only used in experimental settings. Sometimes the models are.

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Tested on sets of pictures that are very carefully chosen but they do not work well in the real world. For example, they might not work well in lighting conditions or if there is a lot of noise in the back-ground. Also the systems that detect diseases are often not connected to systems that monitor the environment or pre-dict crop yields. Another problem with these systems is that they are not very good at working in the cloud. While we know how accurate they are we do not know much about how it takes them to make predictions or how to make them work with other systems. So even though deep learning has helped a lot with classifying plant diseases we still need to figure out how to make these systems work together with smart agriculture systems. Plant disease detection systems need to be able to work with systems that help farmers, and this is something that people are still working on.

E. Limitations of Existing Systems

Smart agriculture research has gotten better with the Inter-net of Things monitoring, machine learning that predicts crops learning that finds diseases and cloud integration. Most systems are not connected they work on their own. The Internet of Things solutions mainly. Show environ-mental data while the models that make predictions often use old data and do not get new information from sensors in real time. The systems that use learning to find diseases are usually separate and just look at pictures they do not

work with crop prediction or cloud-based decision support. Many people who do research focus on making the algo-rithms better, but they do not think enough about how to make them work on a scale, how to keep the cloud integra-tion secure and how to make decisions in real time. There are also problems, like making sure the network is reliable using energy efficiently in the sensor nodes and keeping the data safe. These things are not solved completely. So, we need an agriculture system that is fully connected works on a big scale and is secure. This will help solve the problems and support precision farming that works. Smart agricul-ture needs this kind of system to be useful.

F. Research Gap Identified

When we look at what people have written about smart agri-culture, we can see that a lot of these systems only focus on one thing at a time like using the internet to keep an eye on things using machine learning to guess how well crops will do or using deep learning to figure out if plants are sick.

Not many people have written about a system that puts all of these things together in a way that works smoothly. We need a system that can take in information from sensors in time use that information to make predictions automati-cally figure out what diseases plants have and do all of this on a secure cloud system. A lot of systems do not do a job of combining the information from the internet with smart models and a cloud system that can handle a lot of informa-tion. So there is a gap in research when it comes to making a complete smart agriculture system that combines sensors, intelligence and cloud technology to make precision farm-ing work in a practical and scalable way. Smart agriculture systems need to be able to do all of these things to really help farmers. Smart agriculture is an area that needs a lot of work to make it useful, for people who grow crops.

III. Problem Statement

Farmers generally face problems in predicting the yield of the crop, identifying diseases at an early stage, and se-lecting the appropriate crop for farming. Generally, con-ventional farming practices depend on manual observations and decisions based on experience. This leads to improper predictions and decisions. Farmers also do not get the op-portunity to use advanced technologies that help them get appropriate information and suggestions at the right time. This leads to inefficient farming practices and improper de-cisions. There is a need for the development of an intelli-gent smart farming system using the power of AI, IoT data, and cloud computing.

IV. Objectives Of The Proposed System

The objectives of the proposed smart farming system are as follows:

- To design a cloud computing-based smart agriculture system.

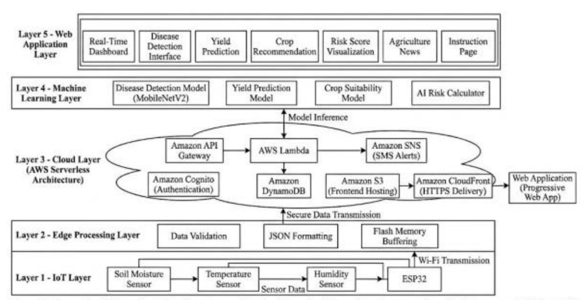

Figure X: Proposed multi-layer Smart Farming system architecture integrating IoT sensing, edge processing with flash memory buffering, AWS serverless cloud services, machine learning models, and a Progressive Web Application interface with automated SMS alert mechanisms.

Figure 1. Proposed Smart Agriculture System Architecture

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- To design a system for predicting crop yield based on environmental and soil parameters.
- To design a plant disease detection model using deep learning techniques.
- To design a model to suggest crops based on environmental and soil parameters.
- To design a real-time monitoring and visualization model using an interactive dashboard.
- To design a notification system to send alerts to farmers regarding potential risks and environmental changes.

A. Primary Objective

The primary objective of this research is to design and de-velop an intelligent smart farming system for farmers to monitor crop health, predict crop yields, and detect crop diseases using artificial intelligence techniques. This system helps farmers to upload images of crop leaves and obtain disease prediction with confidence levels using a deep learning model. In addition, environmental and crop information is analyzed to obtain crop yields and crop recommendations. This helps farmers to make better decisions and improve crop productivity using a cloud-based web platform.

V. Proposed System Architecture

A. Overall System Overview

The Smart Farming system includes various components like IoT devices, edge processing, cloud services, machine learning models, and a web-based app.The system's main job is to watch the environment constantly, analyze the data carefully, and send farmers alerts in a safe and reliable way.Every part of the system has its own role to play.We collect sensor data from the field, then process and store it in the cloud before running machine learning models to analyze it.Finally, we present it to users using an interactive dashboard.This design is set up so many people can use it safely, quickly, and without any trouble.

B. IoT Layer (ESP32 and Sensors)

The focal point of this is the IoT layer, which is based on the ESP32 microcontroller board. This is essentially the "eyes and ears" of this operation.

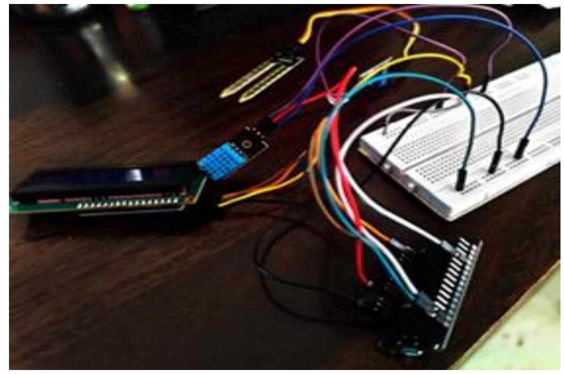

Figure 2. ESP32 Based IoT Sensor Setup

It is connected to a va-riety of sensors that monitor the environment, such as the moisture, temperature, and humidity of the soil. This is not a static operation, however. It is always "beating to the drum," waking up periodically to "take the pulse" of the en-vironment and gathering raw data from the soil and air. In order to keep things simple and neat, this raw data is then transmitted to the cloud via Wi-Fi in a JSON format, which is essentially a "digital list." This is all done through the ESP32, which is the main data collector, ensuring that all of this real-time information is collected correctly. This is not raw data; this is what the entire system is dependent upon to function.

C. Edge Layer Processing

Basic preprocessing occurs at the edge before the data is sent to the cloud. This includes checking the sensor data and ensuring the data is correctly formatted. For the connectivity issue experienced in rural areas, flash memory buffer functionality has been integrated into the ESP32 device. In the event of a lack of internet connectivity, the data collected by the sensor will be stored locally. Once the device has connected to the internet, the data will be uploaded automatically, ensuring the reliability of the system and preventing data loss.

D. Cloud Layer (AWS Services Integration)

The cloud layer is implemented using a serverless architec-ture provided by AWS. This is done to ensure the scalability and availability of the solution. The AWS services used are:

- Amazon API Gateway for the reception of data
- AWS Lambda for the backend processing
- Amazon DynamoDB for storing the sensor and user data
- Amazon S3 for hosting the web application
- Amazon CloudFront for content delivery via HTTPS
- Amazon SNS for sending automated SMS notifications
- Amazon Cognito for authentication

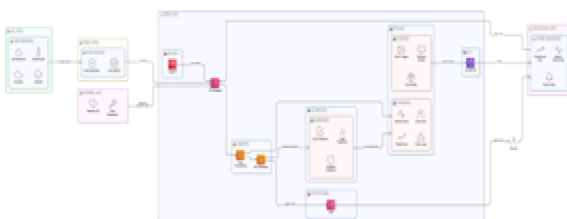

Figure 3. AWS Cloud Architecture for Smart Farming System

With the use of the AWS serverless architecture, the solu-tion can scale automatically. This is advantageous for the utilization of the resources and the handling of the data re-ceived.

E. Machine Learning Model Integration

The system integrates multiple machine learning models for intelligent decision-making purposes:

- A MobileNetV2-based deep learning model for crop disease detection
- A regression model for crop yield prediction
- A classification model for crop suitability recommenda-tions
- An AI-based Risk Calculator for early prediction of dis-ease outbreaks

These models are accessed through API endpoints, and pre-dictions are made in near real-time. **Risk Calculator:** It uses data from IoT sensors, weather forecasts, rainfall pre-diction, growth stages of the crops, and historical patterns of disease occurrences to generate a risk score between 0% and 100%. Accordingly, the system can raise alerts for the farmer regarding the potential risks even before the disease occurs.

F. Web Application Layer

The web application offers a user-friendly interface for the farmer. It has real-time information, prediction, risk visual-ization, crop management, news updates, and usage instruc-tions.

It has been designed as a Progressive Web Applica-tion (PWA), which enables the farmer to access the data even when the internet connection is not available, i.e., the data can be accessed offline if it was previously loaded by the user, and the application can be installed on the mobile device of the farmer even if he/she does not have the app installed, i.e., the app does not require the app store for in-stallation.

G. Security Architecture

The system includes a vital feature: security. The following features have been incorporated in the system:

- User authentication via Amazon Cognito
- Authorization at the device level to ensure data isolation
- HTTPS-based encrypted communication
- Role-based access control for backend services

These features ensure that any user is able to access their own data in a secure manner.

H. Data Flow Explanation

This system utilizes a data flow process, which can be ex-plained as follows:

1. Sensors receive the environmental parameters from the field.
2. ESP32 checks the data and stores the data if necessary.
3. Sending the data to Amazon API Gateway is done se-curely.
4. AWS Lambda receives the data and stores the data in DynamoDB.
5. Machine learning prediction is done on demand.
6. Results are displayed on the web dashboard.
7. If the risk level is above a certain level, the alert is sent through Amazon SNS.

VI. SYSTEM IMPLEMENTATION

A scalable, serverless cloud architecture that incorporates machine learning models was used to implement the sug-gested Cloud-Based AI Smart Agriculture System. AWS deployment, database setup, hardware configuration, soft-ware stack, and API integration are all part of the imple-mentation.

A. Hardware Setup

The following hardware elements were employed in the testing and development process:

- Personal Computer (Intel i5/i7 processor, 8GB+ RAM)
- Stable Internet connectivity
- Smartphone or digital camera for capturing plant leaf images
- Optional: Soil moisture sensors (for future IoT integration)

The architecture is designed to support future IoT-based sensor integration for real-time environmental monitoring.

B. Software Technologies Used

The software implementation includes frontend, backend, and machine learning components.

1) Frontend Technologies :

- HTML5 and CSS3 for user interface design
- JavaScript for client-side logic
- Responsive dashboard interface

2) Backend Technologies :

- Python for server-side processing
- RESTful API architecture
- JSON for data exchange

3) Machine Learning and Deep Learning :

- TensorFlow and Keras for deep learning implementation
- Scikit-learn for regression and classification models
- MobileNetV2 CNN architecture for plant disease detec-tion
- Jupyter Notebook for model training and experimentation

C. AWS Deployment

The entire system was setup on Amazon Web Services (AWS) to provide scalability, reliability, and security. The following AWS services were utilized:

- Amazon Cognito: Access control and user authentication
- Amazon API Gateway: Management of RESTful APIs
- AWS Lambda: Backend computation with no server
- Deployment of machine learning models via Amazon SageMaker
- NoSQL database, Amazon DynamoDB
- Amazon S3: Object storage and static website hosting
- Delivery of secure HTTPS content via Amazon Cloud-Front
- Amazon SNS: Notification and alert system Deployment workflow:
  1. ML models were trained locally using Jupyter Note-book.
  2. In Amazon SageMaker, trained models was set into endpoints.
  3. AWS Lambda functions were configured to invoke SageMaker endpoints.
  4. API Gateway exposed REST APIs for frontend com-munication.
  5. The frontend application was hosted on Amazon S3 and delivered via CloudFront.
  6. User authentication was secured using Amazon Cog-nito.

D. Database and Storage Configuration

The system design incorporates a NoSQL database archi-tecture for scalable and flexible storage solutions. The database stores: User details, Crop prediction history, Disease detection records, Environmental parameters, and Alert logs. DynamoDB was chosen because of its low latency, automatic scaling, seamless integration with AWS Lambda, and flexible schema. Amazon S3 is used to: Host the frontend static website, Store the uploaded plant leaf images (optional extension), and Store the trained model artifacts.

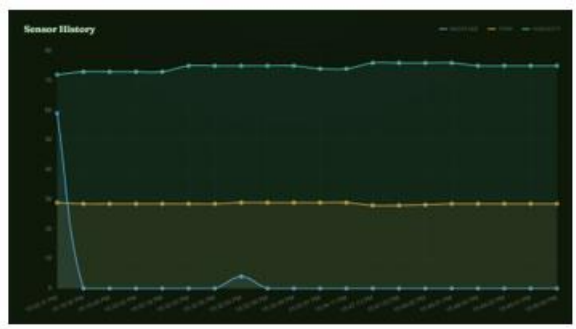

Figure 4. Real-Time Sensor Monitoring Dashboard

E. API Integration

The system uses a RESTful API communication paradigm.

1. User enters input data via the web interface.
2. API Gateway receives the request.
3. API Gateway triggers AWS Lambda.
4. Lambda checks and processes the input data.
5. If ML inference is needed, Lambda calls the Sage-Maker endpoint.
6. Prediction output is received by Lambda.
7. Output is stored in DynamoDB
8. Response is sent back to the frontend in JSON format.
9. If critical conditions are identified, Amazon SNS sends alert notifications.

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VII. RESULTS AND DISCUSSION

A. *Real-Time Monitoring Results*

The Smart Farming system was used to see how well it can monitor things in time. A device called ESP32 was used to collect information about the soil and the air. It collected data on how wet the soil was, how hot or cold it was and how humid the air was. This data was sent to the cloud in a way. The data was then shown on a website so people could see what was going on at the farm from away. Each farmer could only see the data from their devices. The website also showed what the weather was like and what it would be like in the future. The website updated every 30 to 60 seconds so people could see what was happening in real time.

Sometimes the internet does not work well in areas. To deal with this problem the device was able to store data. When the device could not send data to the cloud it stored the data. Sent it when the internet started working again. This way the farm could still be monitored all the time. No data was lost. The Smart Farming system was able to keep monitoring the farm even when there were problems, with the internet.

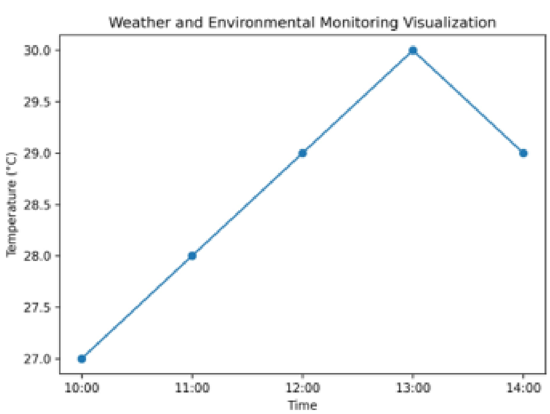

Figure 5. Weather and Environmental Monitoring Visualization

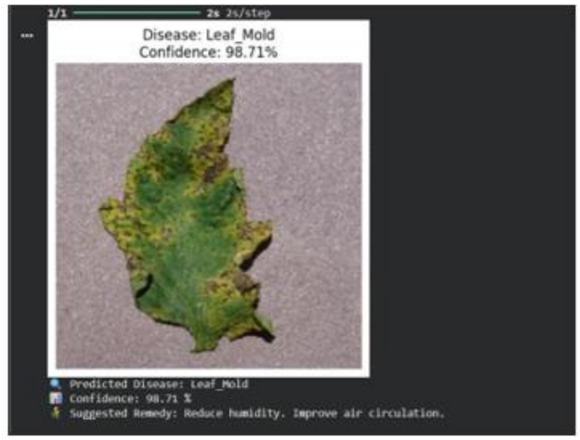

Figure 6. Tomato Leaf Disease Detection using MobileNetV2

B. *Model Performance Evaluation*

Crop Disease Detection:

We built a model using MobileNetV2 that looks at pictures of leaves to see if they are sick. This model does a job. It gets the answer about 94 percent of the time when it is being trained and about 91 percent of the time when it is being tested. This means the Crop Disease Detection model is very good at finding diseases in leaves. The Crop Disease Detection model also tells us how sure it is about its answer. This helps us catch diseases in leaves early.

Crop Yield Prediction:

We built another model to predict the food that a crop will produce. This model uses information like temperature, rainfall, soil moisture and what kind of crop it is. The Crop Yield Prediction model is very good at making predictions. The model achieved an accuracy of 87 per cent. This helps us plan. Make sure we have enough food.

Crop Suitability Recommendation:

We also built a model to help us choose the crops to plant. This model looks at the soil and the weather. Tells us what crops will do well.

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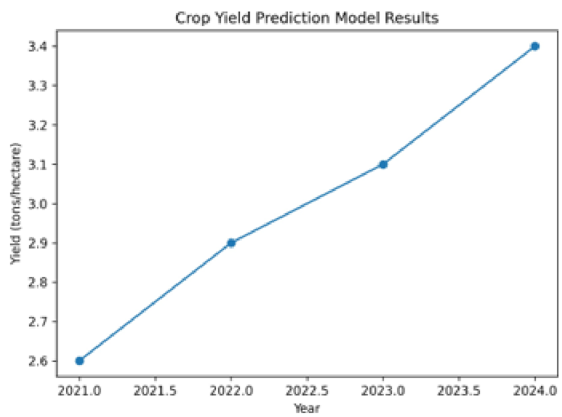

Figure 7. Crop Yield Prediction Model Results

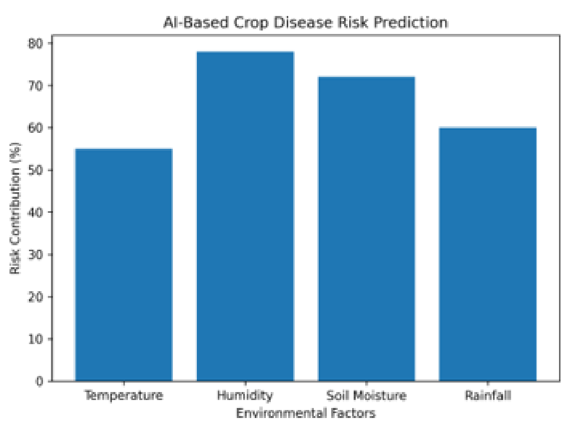

Figure 8. AI-Based Crop Disease Risk Prediction

The Crop Suitability Recommendation model is 88 per cent accurate. This helps us make decisions about what to plant.

TABLE 1.
PERFORMANCE METRICS OF INTEGRATED AI MODELS

Model Type	Training Acc.	Testing Acc.	Primary Function
MobileNetV2 (CNN)	94%	91%	Disease Detection [cite: 585]
Regression Model	–	87%	Yield Prediction
Classification Model	–	88%	Crop Suitability [cite: 600]

AI-Based Risk Calculator:

We created a special calculator that uses artificial intelligence to figure out if a crop is likely to get sick. The AI-Based Risk Calculator looks at a lot of information like the soil, the weather and how the crop is growing. It gives us a score that tells us how likely it is that the crop will get sick. The scores from the AI-Based Risk Calculator are divided into three groups: Low, Moderate and High. For example if the score is 78 percent that means the crop is very likely to get an infection in a days because it is too humid and the soil is too wet. This warning, from the AI-Based Risk Calculator helps us take action before the crop gets sick.

C. System Performance Analysis

We checked the system performance to see how it worked. We wanted to know how long the system took to respond if the system could handle a lot of users and if the system worked well all the time. The system responded quickly. It took the system between 300 and 800 milliseconds to give us an answer. When we used the system for machine learn-ing tasks the system took 2 seconds to finish. The dash-board was really fast too. The dashboard loaded in under 3 seconds when everything was working normally. We used a serverless setup with AWS. This meant the system could handle a lot of users at the time without any problems. The system also sent us SMS alerts when something went wrong with the system. This was helpful because we did not have to watch the system all the time to see if something was wrong, with the system. The system was a Progressive Web Application. This meant the system could work when the internet was not available. The system was also easier to use when the internet was slow. We made sure the system was safe. We made users log in to the system. We used encrypted communication to keep everything. The system performance was good because of the serverless AWS setup and the Progressive Web Application.

D. Comparative Analysis

Traditional farming is about experience. Our system is dif-ferent because it gives farmers the support they need based on data. Our system uses Artificial Intelligence to find dis-eases in crops. It tells farmers which crops to plant. It also forecasts how much they will get from their crops. It pre-dicts the risks that farmers might face. All this information helps farmers plan what to do. Farmers can check on their crops from away. They get messages automatically when something is wrong with their crops.

We keep all the infor-mation on the internet. This makes farming easier. Reduces the amount of crops that are lost. Internet of Things, Artifi-cial Intelligence and cloud computing all work together to provide a solution, for farming. This way of doing things really helps farmers. Our system helps farmers make deci-sions. Farmers can take action to stop their crops from get-ting damaged because they have the information they need. Our system supports farmers by giving them the data they need. Farmers are able to grow crops because of the advice our system gives them.

VIII. CONCLUSION

This paper is about a system that uses the artificial intel-ligence to make farming better. It uses intelligence, deep learning and cloud computing to help farmers grow more food. The system does a things really well:

- It can guess how food a farm will grow using regression models
- It can tell farmers what kind of food is best to grow in a place
- It can find diseases in plants using CNN-based deep learning
- It can show farmers what is happening on their farm in time
- It can keep farmers information safe.

REFERENCES

[1] V. Choudhary, P. Guha, G. Pau, and S. Mishra, "An overview of smart agriculture using internet of things (IoT) and web services," *Environmental and Sustain-ability Indicators*, vol. 26, p. 100607, 2025. [Online]. Available: https://doi.org/10.1016/j.indic.2025.100607

[2] U. A. Avalekar, J. B. Patil, S. T. Patil, J. A. Khot, and K. Prathapan, "Optimizing Agricultural Efficiency: A Fusion Of Iot, Ai, Cloud Computing, And Wireless Sensor Network," *Educational Administration: The-ory and Practice*, vol. 30, no. 5, pp. 10539–10550, 2024. [Online]. Available: https://doi.org/10.2139/ssrn.4789232

[3] B. K. Kuli, J. Debnath, A. Sheikh, S. Das, and P. S. Balai, "Smart Farming Revolution: AI, IoT, and Robotics in Precision Agriculture and Soil Conser-vation," *International Journal of Scientific Research in Science, Engineering and Technology*, vol. 12, no. 2, pp. 688–706, 2025. [Online]. Available: https://doi.org/10.32628/IJSRSET25122193

[4] S. Mansoor *et al.*, "Integration of smart sensors and IOT in precision agriculture, trends, challenges and future prospectives," *Frontiers in Plant Science*, vol. 16, p. 1587869, 2025. [Online]. Available: https://doi.org/10.3389/fpls.2025.1587869

[5] S. Vissarapu, "Al in Agriculture: Cloud-Powered Pre-cision Farming with Real-Time Data Analytics," *Jour-nal of Computer Science and Technology Studies*, 2025. [Online]. Available: https://doi.org/10.32996/jcsts.2025.7.5.37

[6] R. Gong, H. Zhang, G. Li, and J. He, "Edge Computing-Enabled Smart Agriculture: Technical Architectures, Practical Evolution, and Bottleneck Breakthroughs," *Sensors*, vol. 25, no. 17, p. 5302, 2025. [Online]. Available: https://doi.org/10. 3390/s25175302

[7] T. Miller *et al.*, "The IoT and AI in Agriculture: The Time Is Now-A Systematic Review of Smart Sensing Technologies," *Sensors*, vol. 25, no. 12, p. 3583, 2025. [Online]. Available: https://doi.org/10.3390/ s25123583

[8] Ivanochko, M. Gregusˇ, and O. Melnyk, "Smart Farming System Based on Cloud Computing Technologies," *Procedia Computer Science*, vol. 238, pp. 857–862, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050924013395

[9] M. Junaid *et al.*, "Smart Agriculture Cloud Using AI Based Techniques," *Energies*, vol. 14, no. 16, p. 5129, 2021. [Online]. Available: https://doi.org/10. 3390/en14165129